

A PHYSICS-BASED MODELING FRAMEWORK FOR PROGNOSTIC STUDIES

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Prognostics CoE



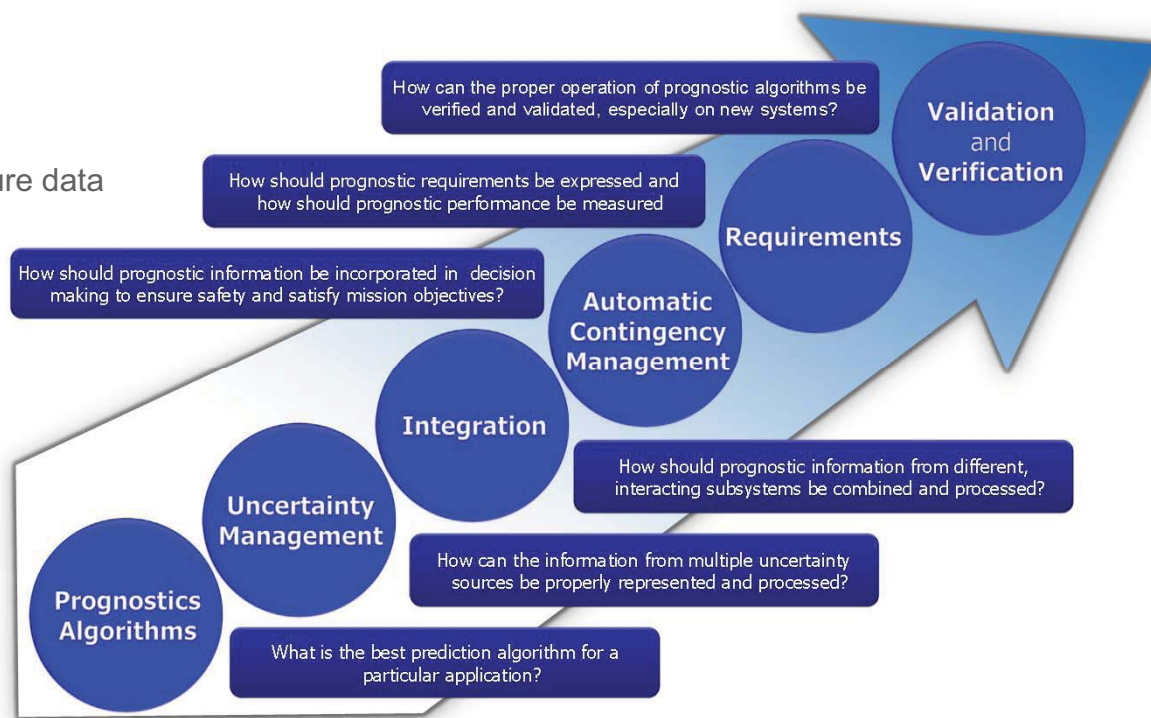
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TECHNOLOGIES

Prognostics Center of Excellence

NASA Ames Research Center, CA

Mission: Advance state-of-the-art in prognostics technology development

- Investigate algorithms for estimation of remaining life
 - Investigate physics-of-failure
 - Model damage initiation and propagation
 - Investigate uncertainty management
- Validate research findings in hardware testbeds
 - Hardware-in-the-loop experiments
 - Accelerated aging testbeds
 - HIL demonstration platforms
- Disseminate research findings
 - Public data repository for run-to-failure data
 - Actively publish research results
- Engage research community



Introduction to Prognostics

Outline

Today we will discuss...

- What is prognostics?
 - It's relation to health management
 - Significance to the decision making process
- How is prognostics used?
 - Reliability
 - Scheduled maintenance – based on reliability
 - Kinds of prognostics – interpretation & applications
 - Type I, Type II, and Type III prognostics
 - Various application domains
- Condition based view of Prognostics
- Prognostic Framework

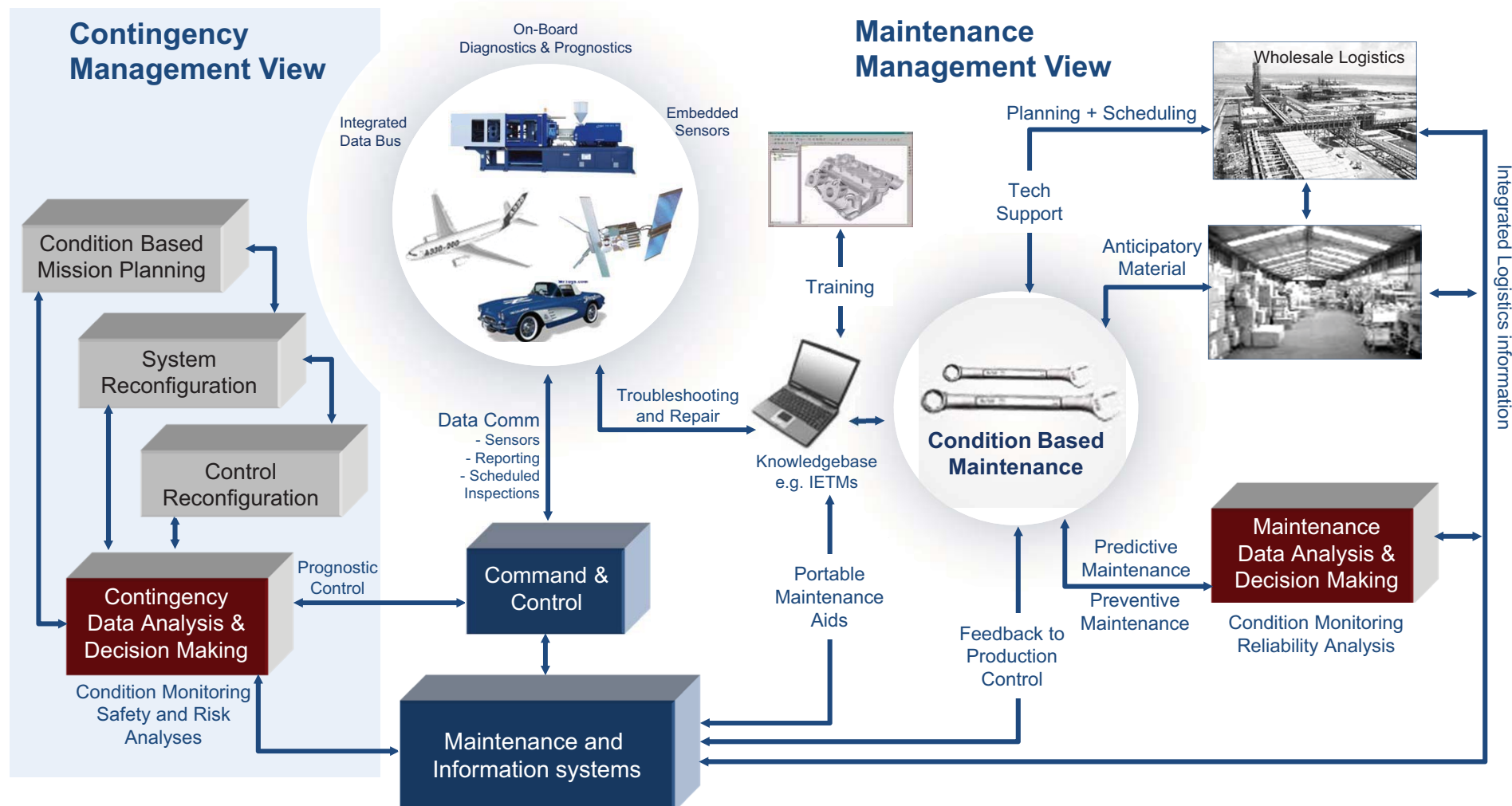
Also...

- What are the key ingredients for prognostics
 - Requirements specifications – Purpose
 - Cost-benefit-risk
 - Condition Monitoring Data – sensor measurements
 - Collect relevant data
 - Prognostic algorithm
 - Tons of them - examples
 - Fault growth model (physics based or model based)
 - Run-to-failure data
- Challenges in Validation & Verification
 - Performance evaluation
 - Uncertainty
 - representation, quantification, propagation, and management

Prognostics and Health Management

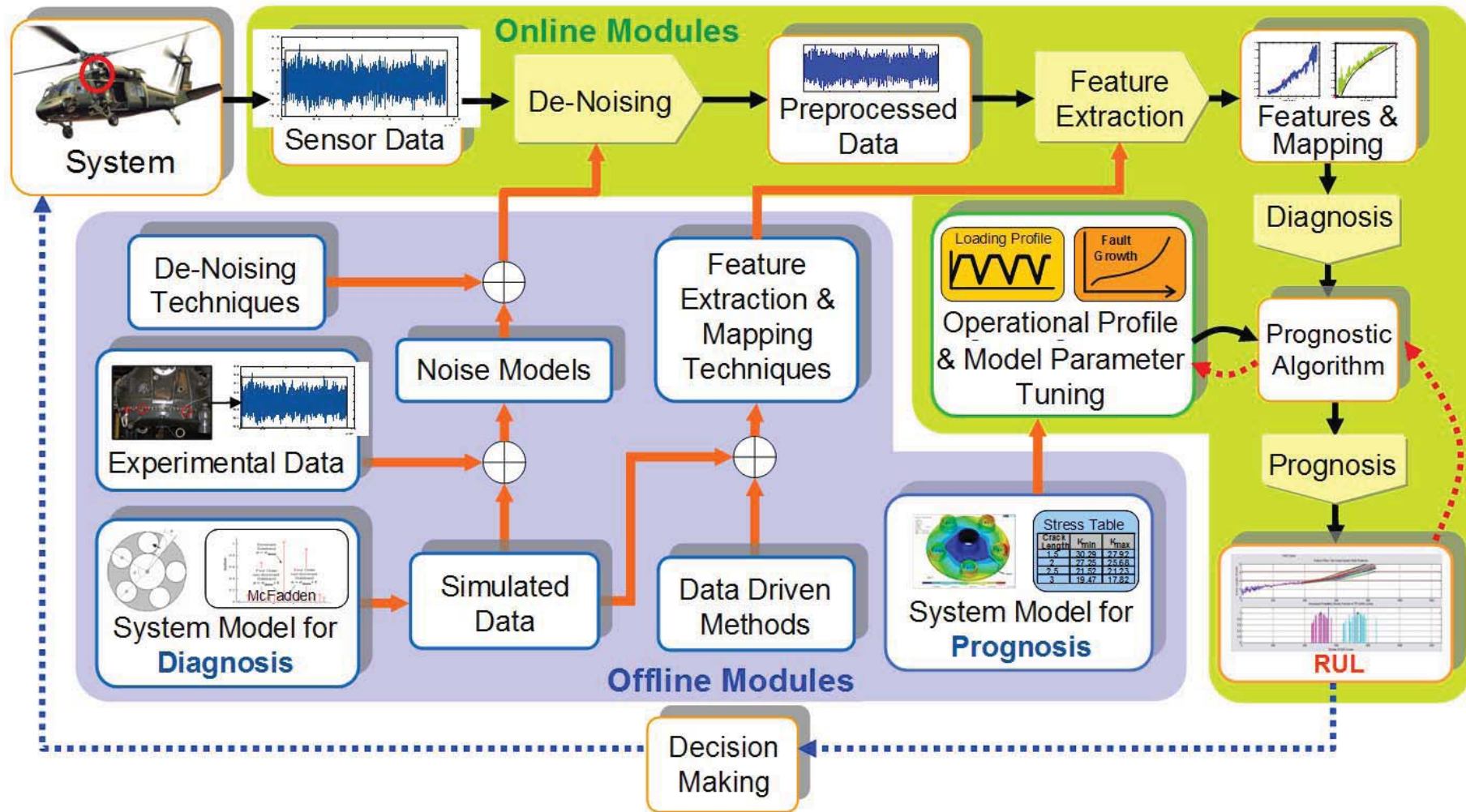
The Perspective

Health Management



- Schematic adapted from: A. Saxena, *Knowledge-Based Architecture for Integrated Condition Based Maintenance of Engineering Systems*, PhD Thesis, Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta May 2007.
- Liang Tang, Gregory J. Kacprzynski, Kai Goebel, Johan Reimann, Marcos E. Orchard, Abhinav Saxena, and Bhaskar Saha, *Prognostics in the Control Loop*, Proceedings of the 2007 AAAI Fall Symposium on Artificial Intelligence for Prognostics, November 9-11, 2007, Arlington, VA.

Data Analysis & Decision Making



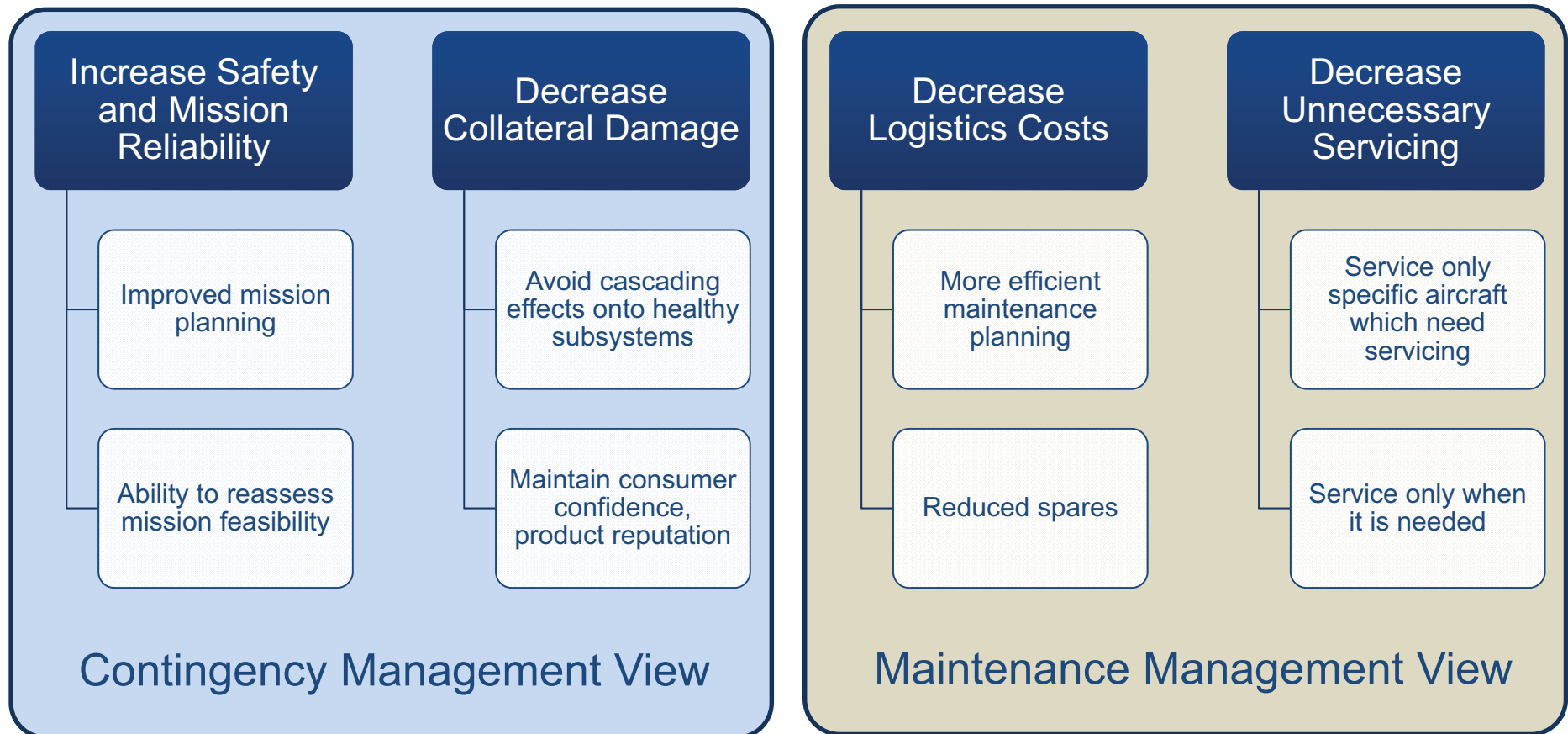
• Adapted from presentations and publications from Intelligent Control Systems Lab, Georgia Institute of Technology, Atlanta [<http://icsl.gatech.edu/>]

Prognostics

- Dictionary definition – “foretelling” or “prophecy”
- PHM definition –
“***Estimation of remaining life of a component or subsystem***”
- Prognostics evaluates the *current health* of a component and, conditional on *future load* and *environmental exposure*, estimates at what time the component (or subsystem) will no longer operate within its *stated specifications*.
- These predictions are based on
 - Analysis of failure modes (FMECA, FMEA, etc.)
 - Detection of early signs of wear, aging, and fault conditions and an assessment of current damage state
 - Correlation of aging symptoms with a description of how the damage is expected to increase (“damage propagation model”)
 - Effects of operating conditions and loads on the system

Goals for Prognostics

What does prognostics aim to achieve?



- Prognostics goals should be defined from users' perspectives
- Different solutions and approaches apply for different users

User Centric View on Prognostics Goals

Category	End User	Goals	Metrics
Operations	Program Manager	Assess the economic viability of prognosis technology for specific applications before it can be approved and funded	Cost-benefit type metrics that translate prognostics performance in terms of tangible and intangible cost savings
	Plant Manager	Resource allocation and mission planning based on available prognostic information	Accuracy and precision based metrics that compute RUL estimates for specific UUTs. Such predictions are based on degradation or damage accumulation models
	Operator	Take appropriate action and carry out re-planning in the event of contingency during mission	Accuracy and precision based metrics that compute RUL estimates for specific UUTs. These predictions are based on fault growth models for critical failures
	Maintainer	Plan maintenance in advance to reduce UUT downtime and maximize availability	Accuracy and precision based metrics that compute RUL estimates based on damage accumulation models
Engineering	Designer	Implement the prognostic system within the constraints of user specifications. Improve performance by modifying design	Reliability based metrics to evaluate a design and identify performance bottlenecks. Computational performance metrics to meet resource constraints
	Researcher	Develop and implement robust performance assessment algorithms with desired confidence levels	Accuracy and precision based metrics that employ uncertainty management and output probabilistic predictions in presence of uncertain conditions
Regulatory	Policy Makers	To assess potential hazards (safety, economic, and social) and establish policies to minimize their effects	Cost-benefit-risk measures, accuracy and precision based measures to establish guidelines & timelines for phasing out of aging fleet and/or resource allocation for future projects

- Saxena, A., Celaya, J., Saha, B., Saha, S., Goebel, K., "Metric
- Wheeler, K. R., Kurtoglu, T., & Poll, S. (2009). A Survey of Health

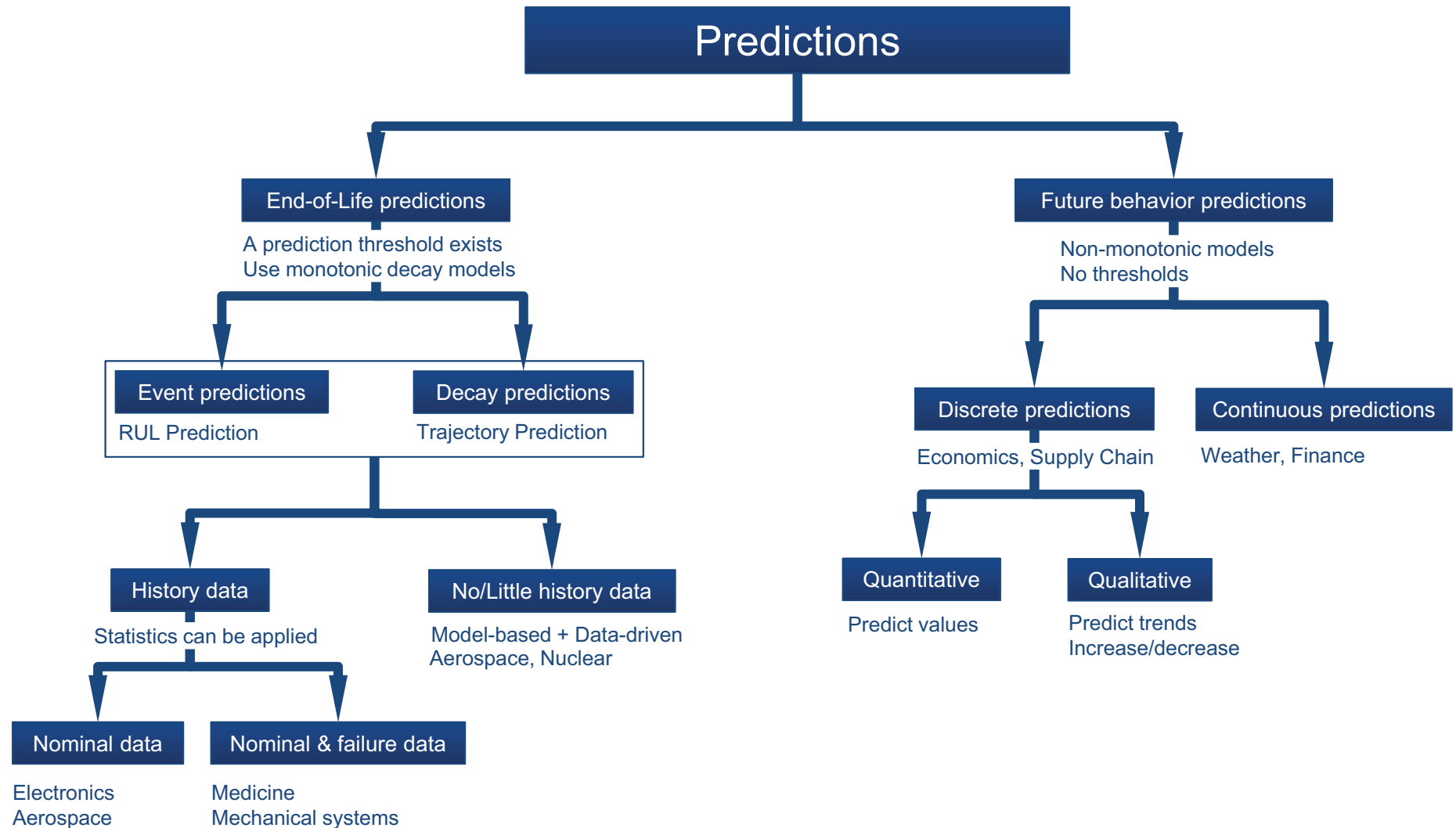
Conferences and Computers and Information in Engineering Conference (IDETC/CIE), San Diego, CA

Prognostics Categories

- **Type I: Reliability Data-based**
 - Use population based statistical model
 - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of a typical component under nominal usage conditions
 - Example: Weibull Analysis
- **Type II: Stress-based**
 - Use population based fault growth model – learnt from accumulated knowledge
 - These methods also consider the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions
 - Example: Proportional Hazards Model
- **Type III: Condition-based**
 - Individual component based data-driven model
 - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions
 - Example: Cumulative Damage Model, Filtering and State Estimation

• For more details please refer to last year's PHM09 tutorial on Prognostics by Dr. J. W. Hines: [<http://www.phmsociety.org/events/conference/phm/09/tutorials>]

Forecasting Applications

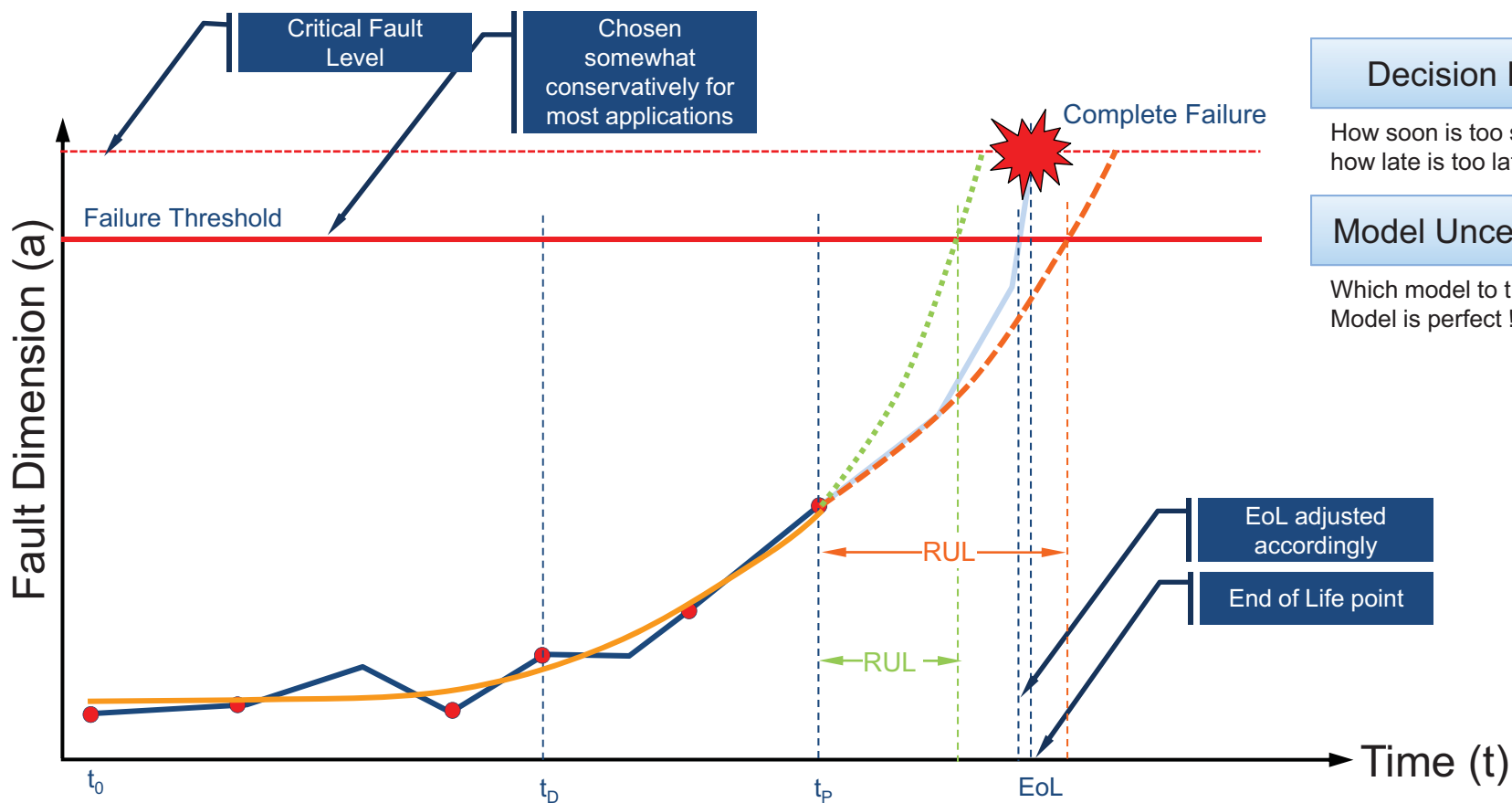


- Saxena, A., Celaya, J., Saha, B., Saha, S., Goebel, K., "Metrics for Offline Evaluation of Prognostics Performance", International Journal of Prognostics and Health Management (IJPHM), vol.1(1) 2010.
- Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., and Schwabacher, M., "Metrics for Evaluating Performance of Prognostics Techniques", 1st International Conference on Prognostics and Health Management (PHM08), Denver CO, pp. 1-17, Oct 2008.

Predicting Remaining Useful Life

Understanding the Prognostic Process

Prognostics Framework



Decision Risk

How soon is too soon and how late is too late?

Model Uncertainty

Which model to trust? No Model is perfect !

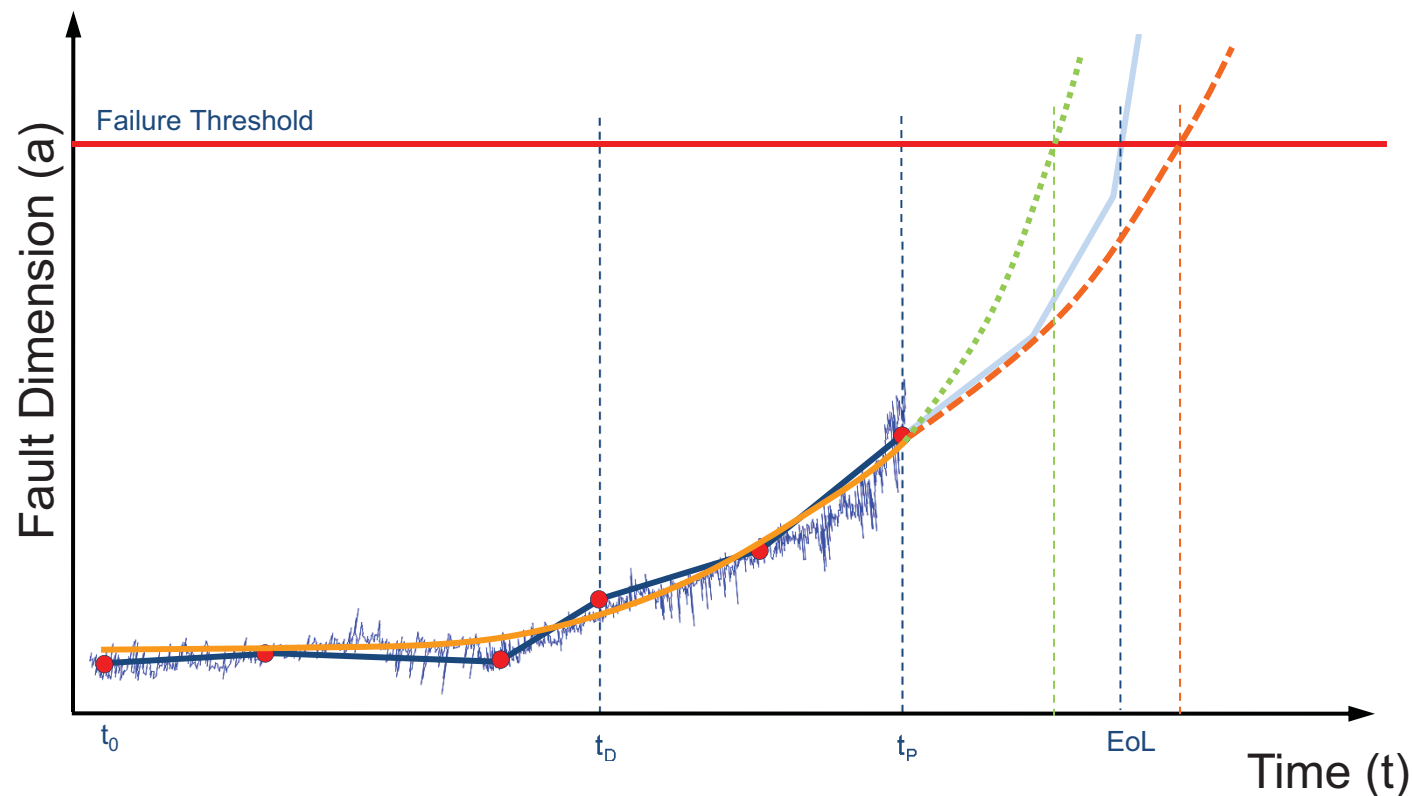
Prognostics Framework

We hardly have access to ground truth

Instead we have measurements, appropriate features of which may correlate to damage. such data are usually noisy!

We use these data to learn the model, which may be noisy

Noise may have a significant effect on the learnt model...



Decision Risk

How soon is too soon and how late is too late?

Model Uncertainty

Which model to trust? No Model is perfect !

No Ground Truth

Ground truth measurements are hard to come by

Noisy Data

Measurement noise leads to more uncertainty!

Uncertainties in Prognostics

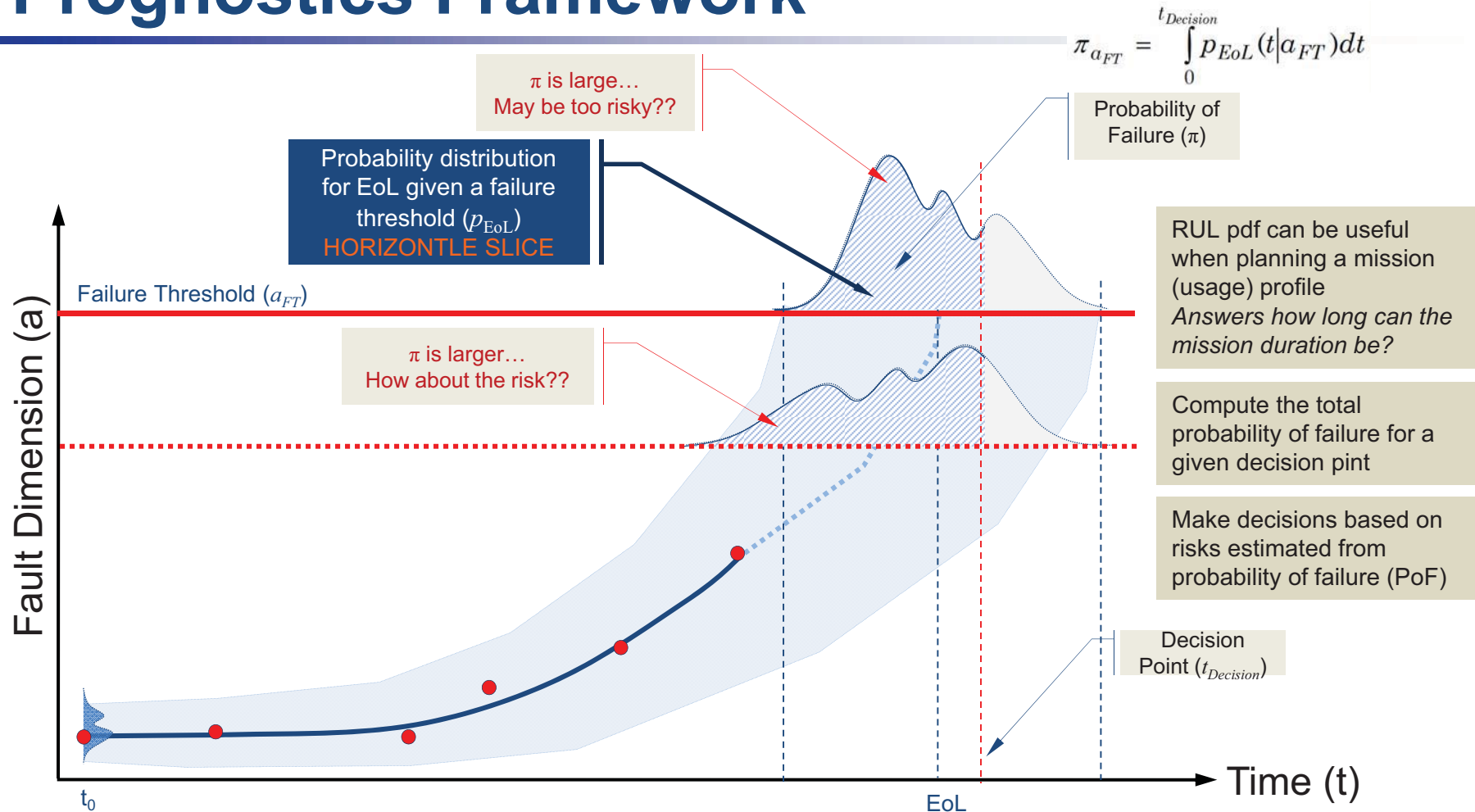
- Uncertainties arise from a variety of sources
 - Modeling uncertainties – **Epistemic**
 - Numerical errors
 - Unmodeled phenomenon
 - System model & Fault propagation model
 - Input data uncertainties – **Aleatoric**
 - Initial state (damage) estimate
 - Variability in the material
 - Manufacturing variability
 - Measurement uncertainties – **Prejudicial**
 - Sensor noise
 - Sensor coverage
 - Loss of information during preprocessing
 - Approximations and simplifications
 - Operating environment uncertainties – *Combination*
 - Unforeseen future loads
 - Unforeseen future environments
 - Variability in the usage history data

Unknown level of uncertainties arising due lack of knowledge or information

Inherent statistical variability in the process that may be characterized by experiments

Unknown level of uncertainties arising due to the way data are collected or processed

Prognostics Framework

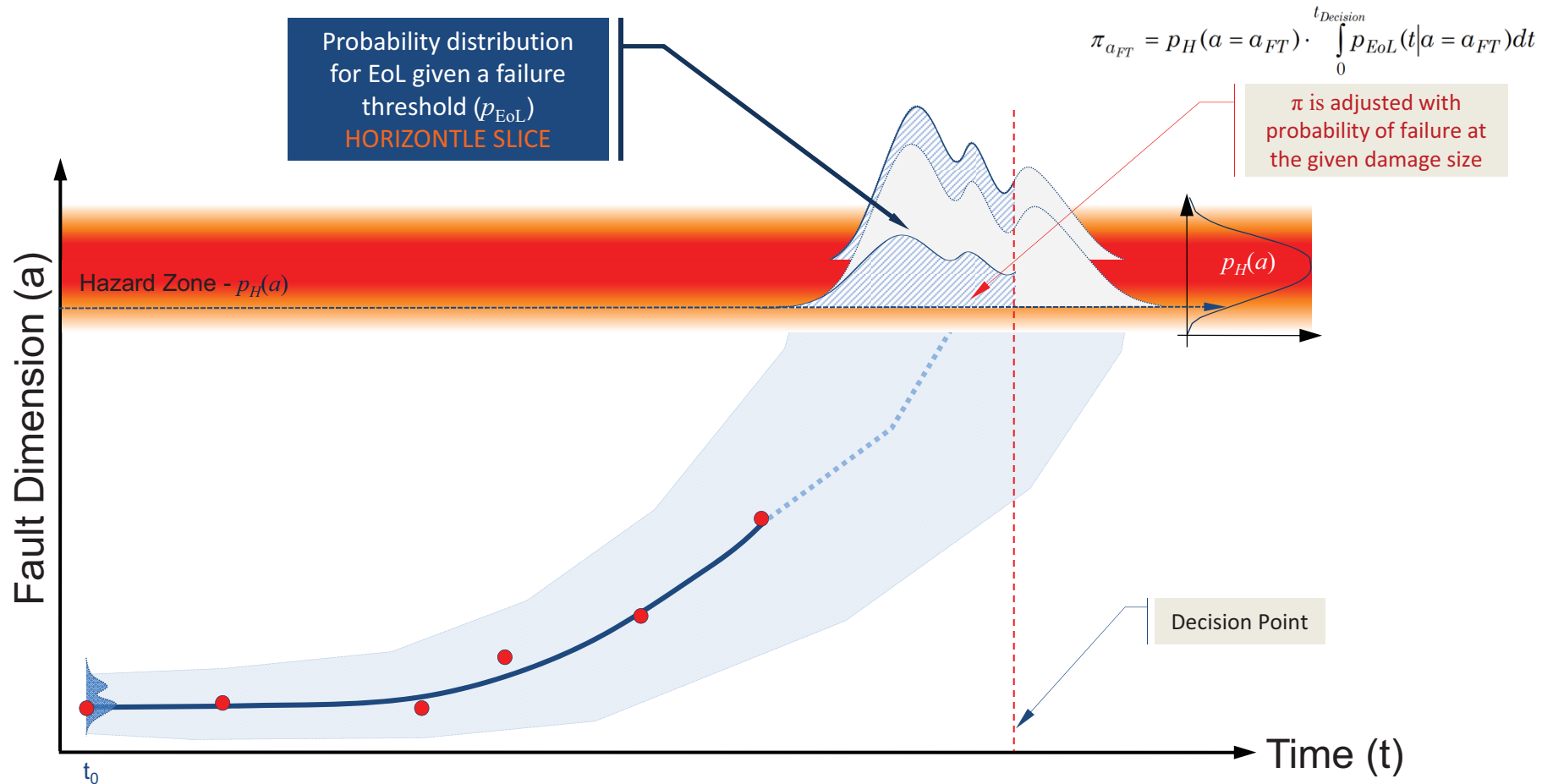


These uncertainties can be represented as a probability distribution on the initial state.
Probability distribution need not be Normal "always".

we can propagate the learnt model along with a confidence bound until the Failure Threshold is reached

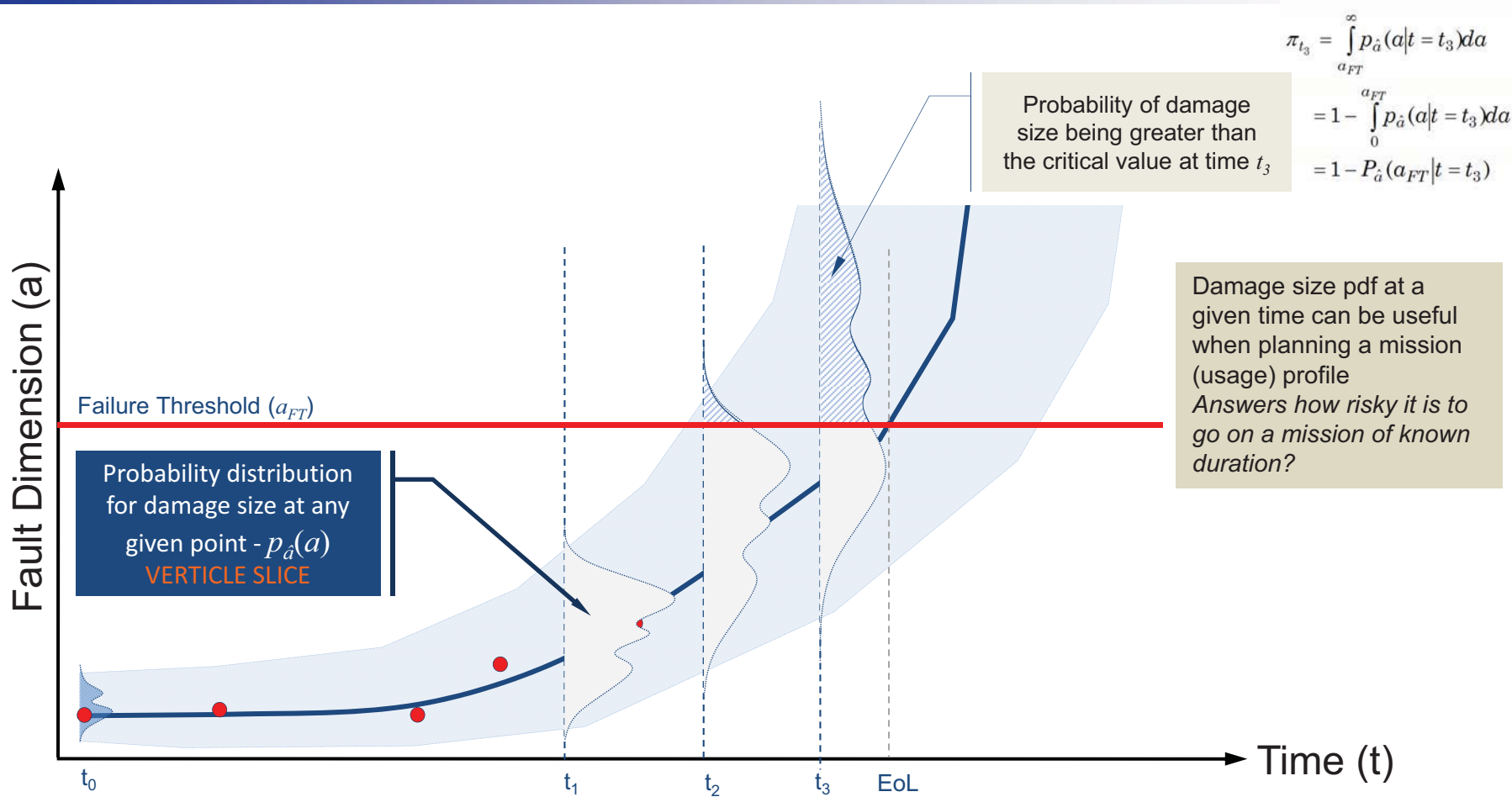
The Horizontal slice tells us when the system can be expected to reach a specified failure threshold given "all" uncertainties considered

Prognostics Framework



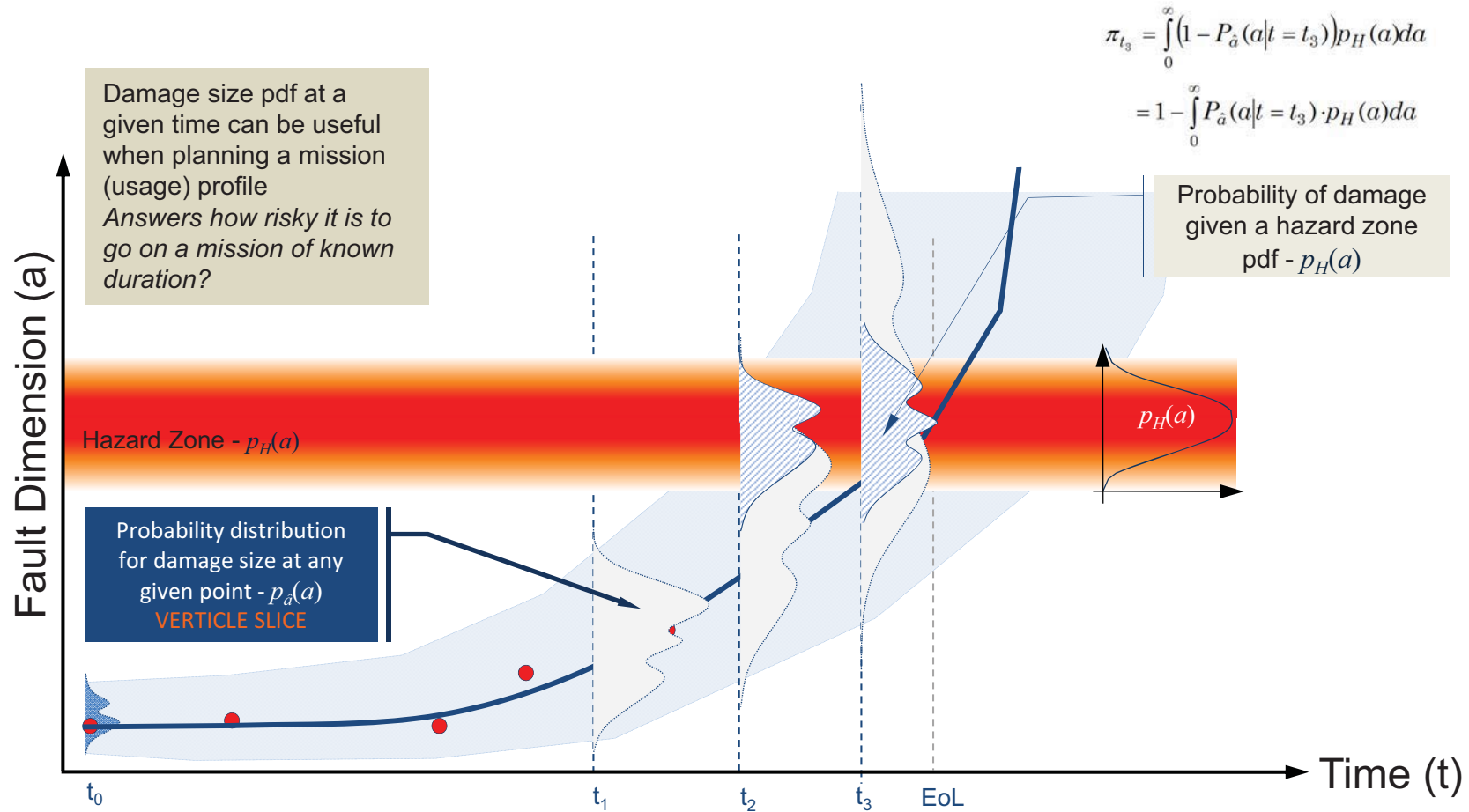
Risk is now a compound function of chosen failure threshold and the decision point

Prognostics Framework



We can figure out if the system would withstand by the time mission is completed

Prognostics Framework



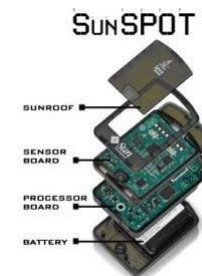
We can figure out if the system would withstand by the time mission is completed

Examples

Prognostics Applications

Application Examples

- Electro-Mechanical Actuators
- Electrochemical Storage
- Electronics
- Valves, Pumps
- Composite Materials
- Solid Rocket Motor Casing
- Rover
- UAV
- Distributed Health Management



Setting up the Problem

Prognostics Modeling

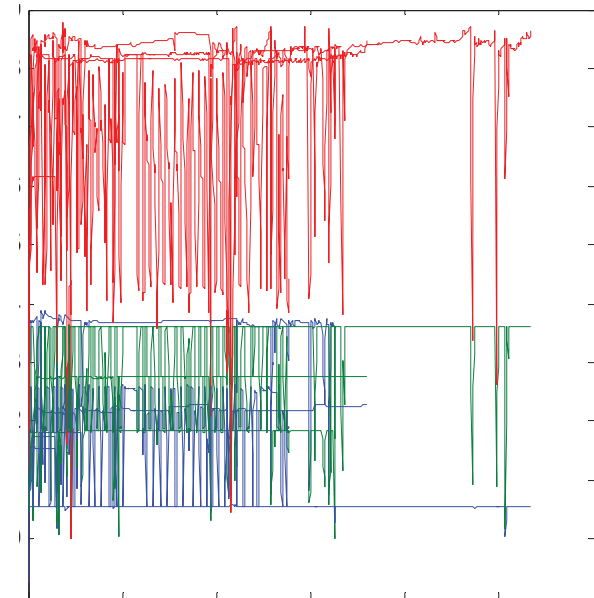
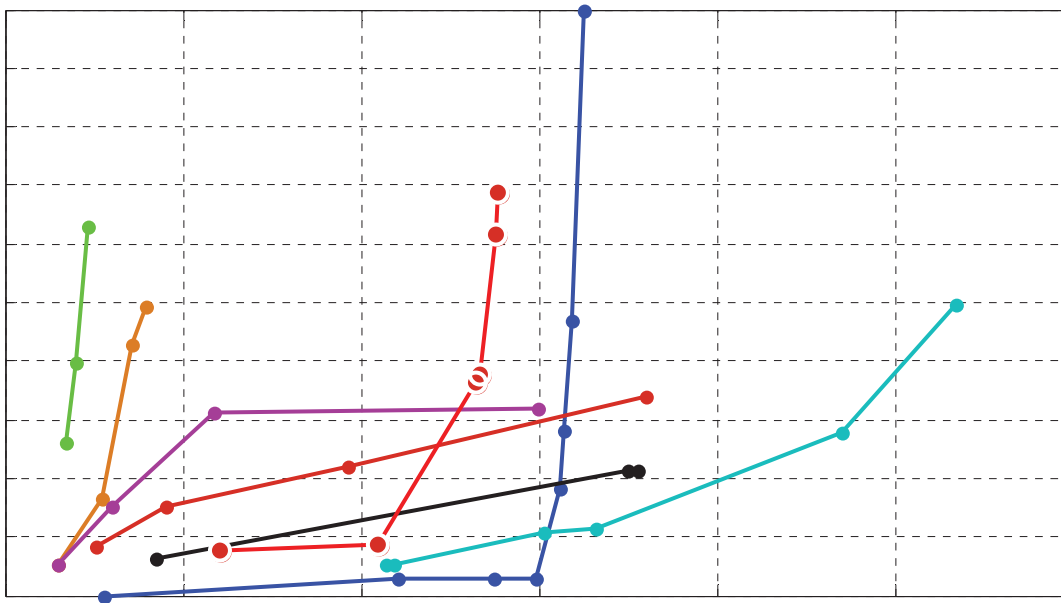
Data-Driven Prognostic Methods

Primarily use data obtained from the system for predicting failures

- What kind of data?
 - Something that indicates a fault and fault growth or is expected to influence fault growth
 - Sensor measurement to assess system state
 - Sensor measurements and communication logs to identify operational modes and operational environment
 - Process data to extract features that “clearly” indicate fault growth
 - Preferably monotonically changing since faults are expected to grow monotonically
 - Predictions can be made in many ways
 - Use raw measurement data to map onto RULs
 - Use processed data to trend in feature domain, health index domain, or fault dimension domain against a set threshold
- How?
 - Learn a mathematical model to fit changing observations
 - Regression or trending
 - Learnt model may not be transparent to our understanding but explains observed data
 - Use statistics if volumes of run-to-failure data is available
 - Map remaining useful life to various faulty states of the system
 - Reliability type RUL estimates

Example - Data-Driven Prognostics Model

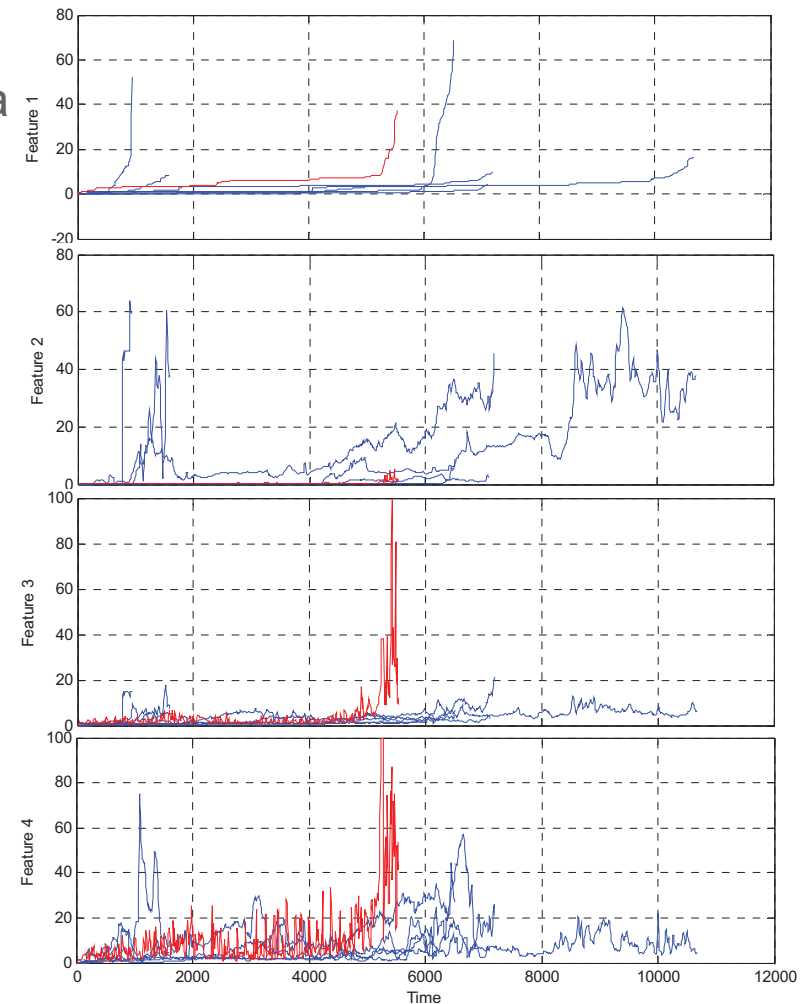
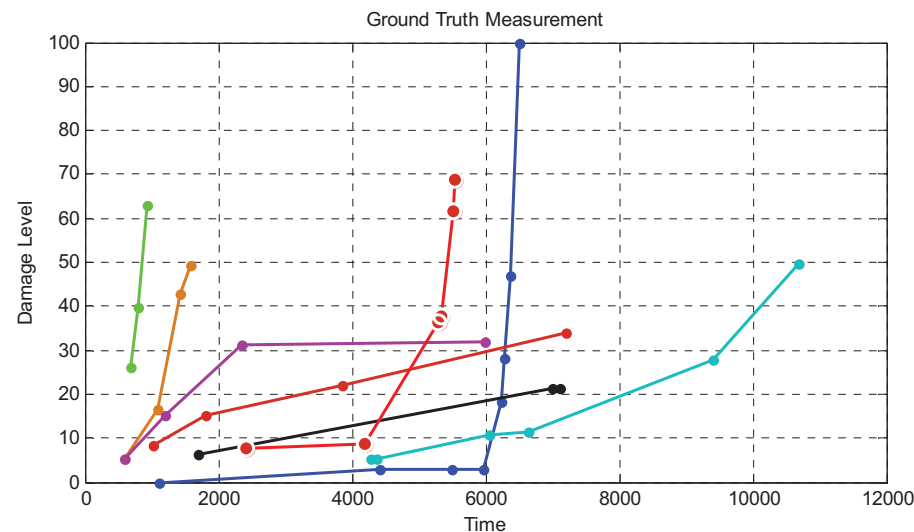
- Operational conditions
 - Indicate level of stress on the system
- Ground truth measurements
 - Ground truth measurements are less frequent



Operational conditions seem to make an impact on how fast the damage grows !

Example - Data-Driven Prognostics Model

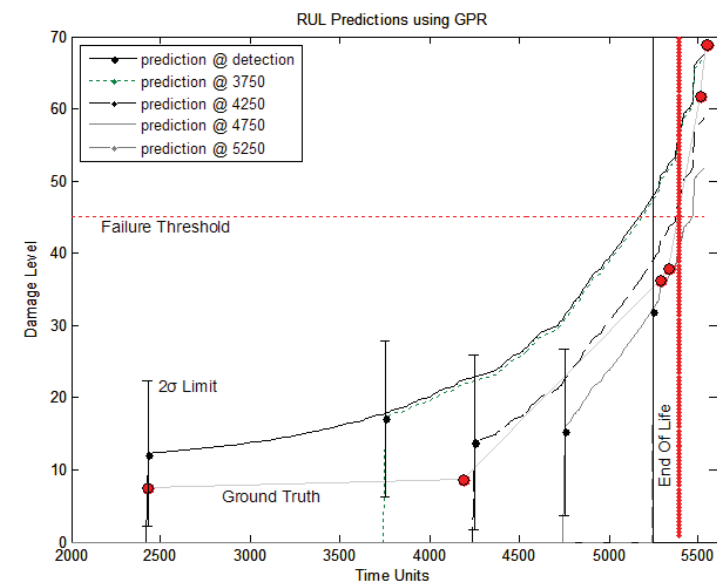
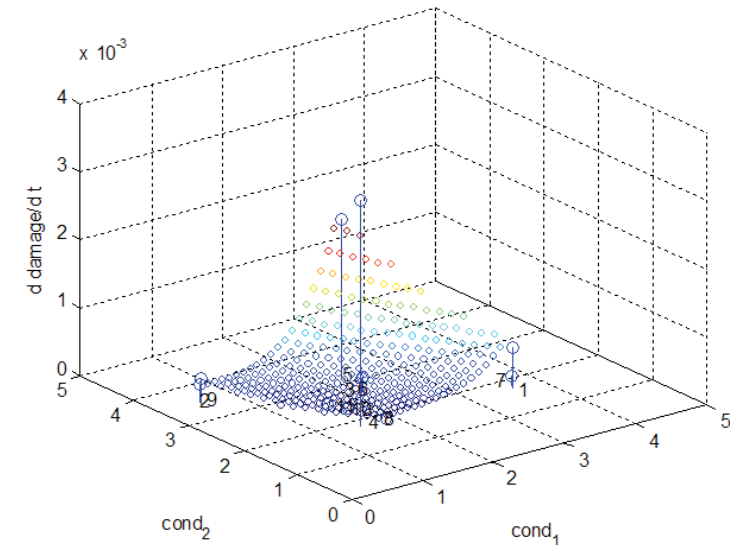
- Sensor Measurements
 - Features are extracted from sensor data
 - Depending on what is measured features will have noise w.r.t. damage growth
 - All run-to-failure units follow their own track



Generally speaking features indicate the level of damage at any given time

Approach

- Learning/training
 - Learn a mapping (M1) between features and the damage state
 - Learn a mapping (M2) between operational conditions and damage growth rate
- Prediction
 - At any given time use M1 & latest measurements to estimate damage state
 - Assuming a future load profile (if unknown) estimate damage accumulation for all future instants using M2



- Goebel, K., Saha, B., and Saxena, A., "A Comparison of Three Data-Driven Techniques for Prognostics", Proceedings of the 62nd Meeting of the Society For Machinery Failure Prevention Technology (MFPT), pp. 119-131, Virginia Beach VA, May 2008

Data-Driven Prognostic Methods

- Advantages

- Relatively Simple to implement and faster
 - Variety of generic data-mining and machine learning techniques are available
- Helps gain understanding of physical behaviors from large amounts of data
 - These represent facts about what actually happened all of which may not be apparent from theory

- Disadvantages

- Physical cause-effect relationships are not utilized
 - E.g. different fault growth regimes, effects of overloads or changing environmental conditions
- Difficult to balance between generalization and learning specific trends in data
 - Learning what happened to several units on average may not be good enough to predict for a specific unit under test
- Requires large amounts of data
 - We never know if we have enough data or even how much is enough

- Examples

- Regression
- Neural Networks (NN)
 - RNN, ARNN, RNF
- Gaussian process regression (GPR)
- Bayesian updates
- Relevance vector machines (RVM)

Physics-Based Models for Prognostics

Use fault propagation models to estimate time of failure

- What kind of models?
 - A model that explains the failure mode of interest
 - A model that maps the effects of stressors onto accumulation of damage – Physics of failure driven
 - e.g. fatigue cycling increases the crack length, or continuous usage reduces the battery capacity over a long term can be modeled in a variety of ways
 - Finite Element Models
 - Empirical models
 - High fidelity simulation models, etc.
 - Modeled cause-effect phenomenon may be directly observable as a fault or not
 - Structural cracks are observable faults
 - Internal resistance changes in a battery causing capacity decay are not directly observable
- How?
 - Given the current state of the system simulate future states using the model
 - Recursive one step ahead prediction to obtain k-steps ahead prediction
 - Propagate fault until a predefined threshold is met to declare failure and compute RUL

Physics-Based Models for Prognostics

- Advantages

- Prediction results are intuitive based on modeled case-effect relationships
 - Any deviations may indicate the need to add more fidelity for unmodeled effects or methods to handle noise
- Once a model is established, only calibration may be needed for different cases
- Clearly drives sensing requirements
 - Based on model inputs, its easy to determine what needs to be monitored

- Disadvantages

- Developing models is not trivial
 - Requires assumptions regarding complete knowledge of the physical processes
 - Parameter tuning may still require expert knowledge or learning from field data
- High fidelity models may be computationally expensive to run, i.e. impractical for real-time applications

- Examples

- Population growth models like Arrhenius, Paris, Eyring, etc.
- Coffin-Manson Mechanical crack growth model

Hybrid Approaches

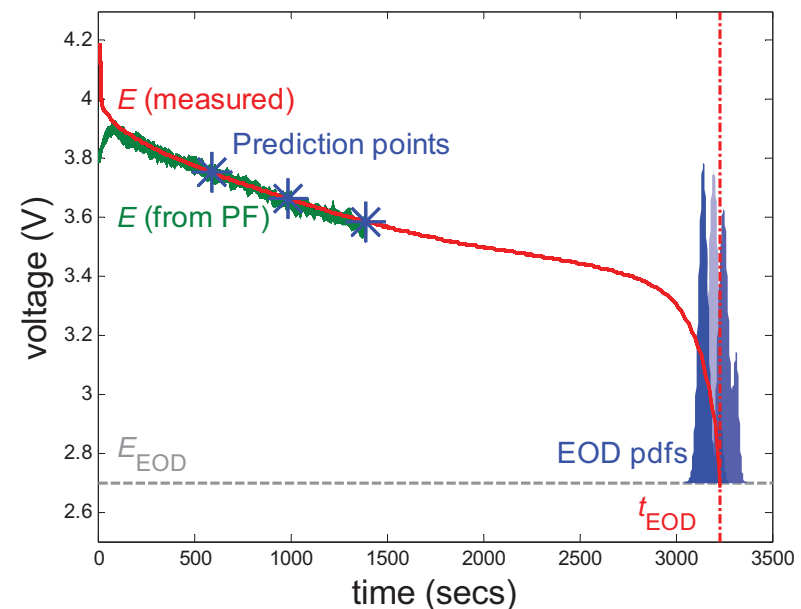
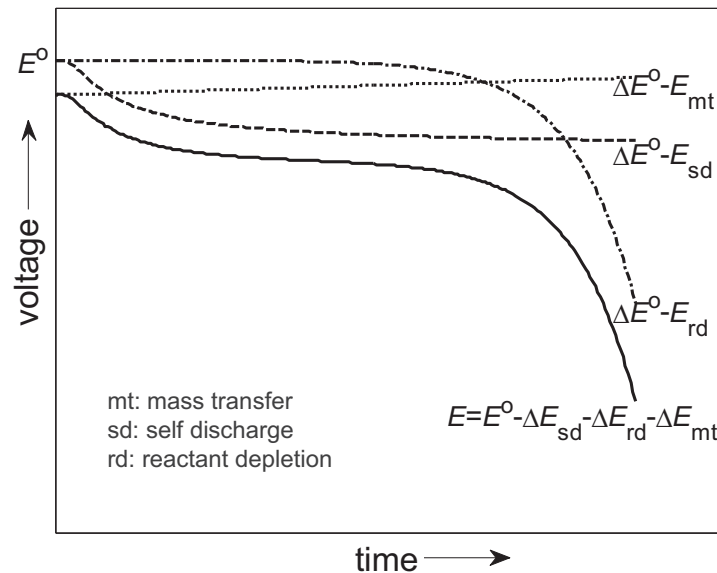
Use knowledge about the physical process and information from observed data together

- How?
 - Learn/fine-tune parameters in the model to fit data
 - Use model to make prediction and make adjustment based on observed data
 - Learn current damage state from data and propagate using model
 - Use knowledge about the physical behavior to guide learning process from the data
 - Improve initialization parameters for learning
 - Decide on the form for a regression model
 - Use understanding from data analysis to develop models
 - Discover the form of the fault growth model
 - Fuse estimates from two different approaches
 - *or any other creative way you can think of...*

Example1 – Physics Model Tuned with Data

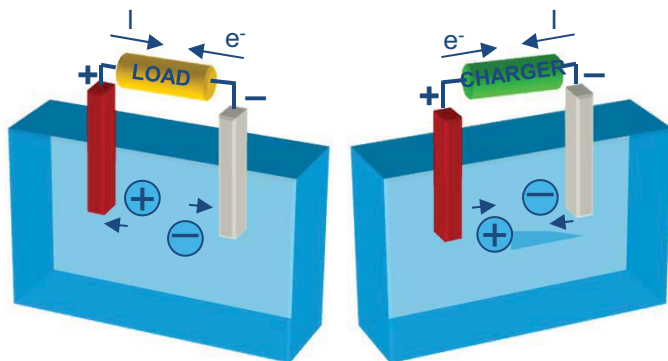
Predicting Battery Discharge – Short Term

- Objective: Predict when Li-ion battery voltage will dip below 2.7 volts
- Hybrid approach using Particle Filter
 - Model non-linear electro-chemical phenomena that explain the discharge process
 - Learn model parameters from training data
 - Let the PF framework fine tune the model during the tracking phase
 - Use the tuned model to predict EOD



- Data Source: NASA PCoE Data Repository [<http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/>]
- B. Saha, K. Goebel, *Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework*, Proceedings of Annual Conference of the PHM Society 2009

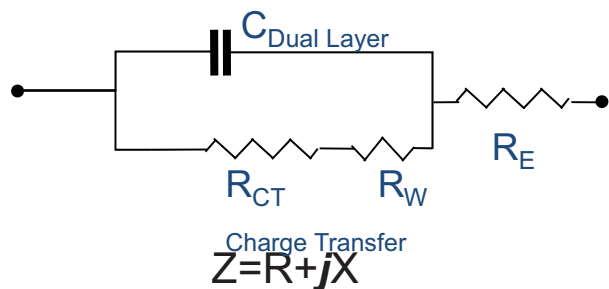
Example2 – Develop Empirical Model from Data



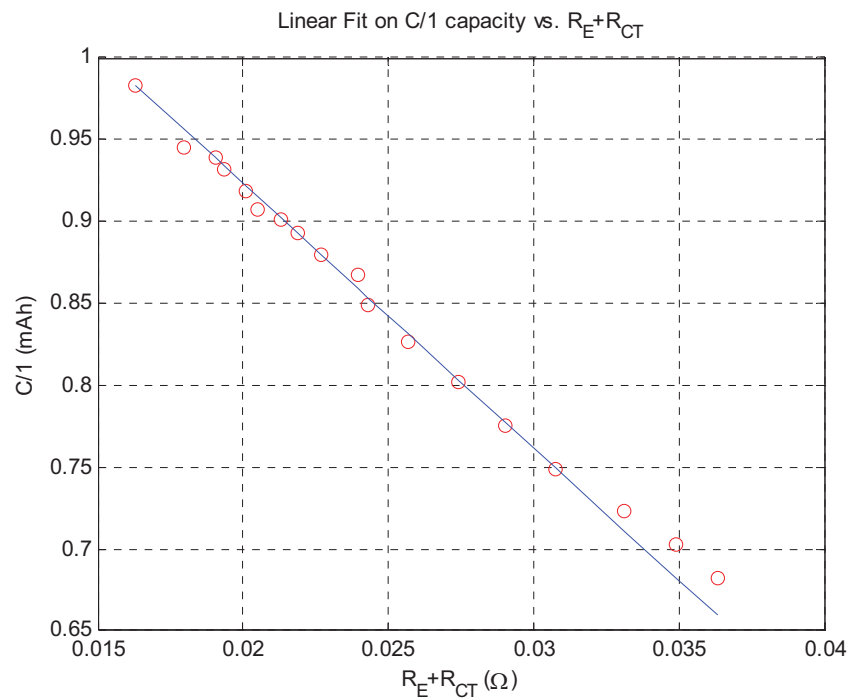
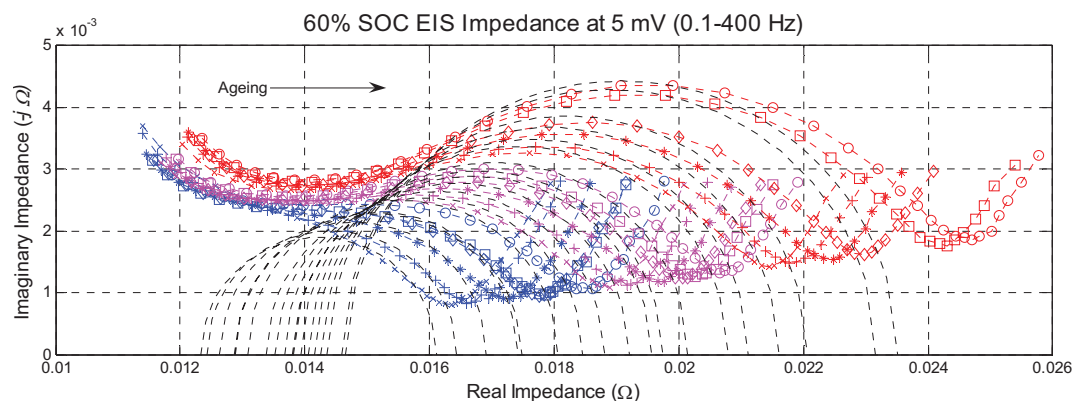
DISCHARGE

CHARGE

Battery Schematic



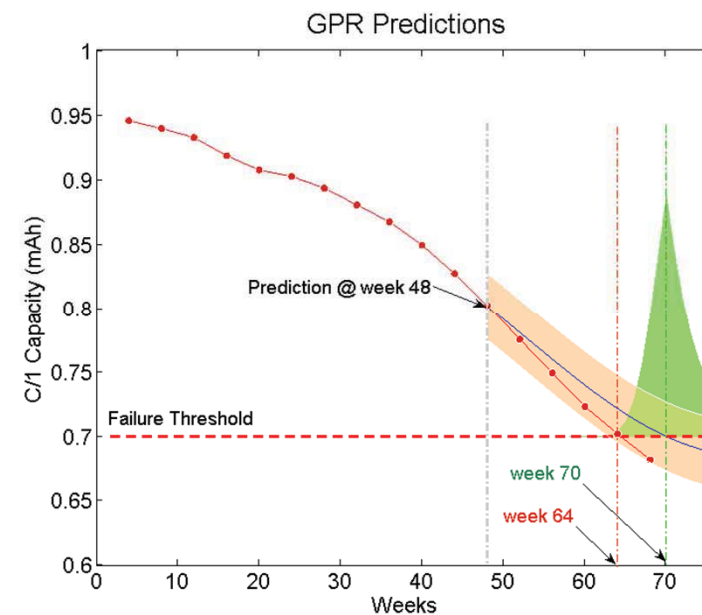
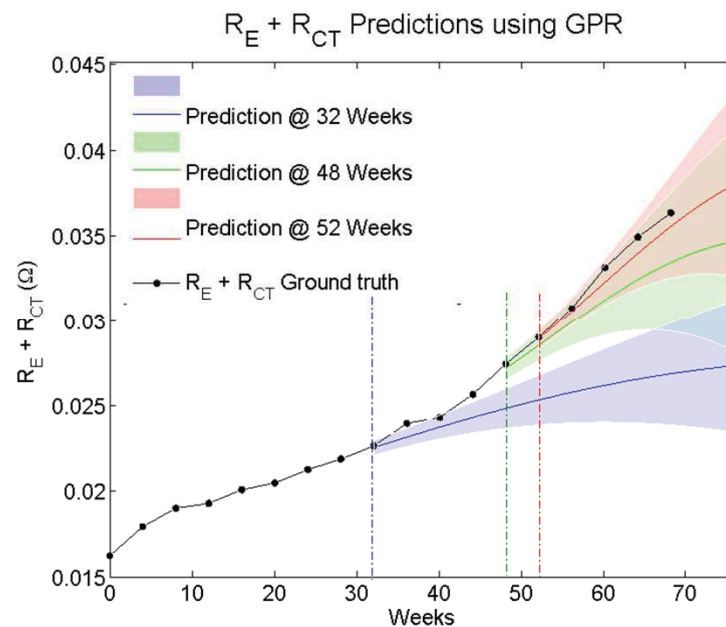
Lumped Parameter Model



Source: Goebel, K., Saha, B., Saxena, A., Celaya, J. R., Christopherson, J. P., "Prognostics in Battery Health Management", IEEE Instrumentation and Measurement Magazine, Vol. 11(4), pp. 33-40, August 2008

Example2 – Data-driven Regression

- Use a regression algorithm to make predictions
 - Gaussian Process Regression



Hybrid Approaches

- Advantages

- Does not necessarily require high fidelity models or large volumes of data – works in a complementary fashion
- Retains intuitiveness of a model but explains observed data
- Helps in uncertainty management
- Flexibility

- Disadvantages

- Needs both data and the models
- An incorrect model or noisy data may bias each other's approach

Otherwise, it's a compromise to get the best out of both so any disadvantage may be alleviated

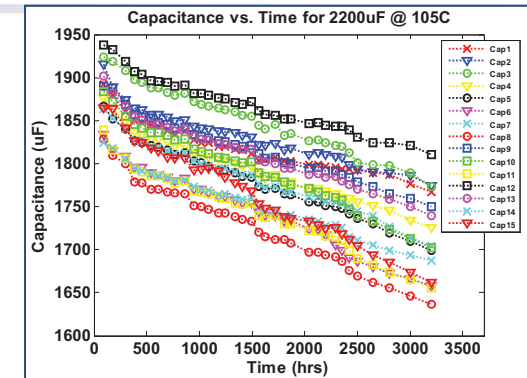
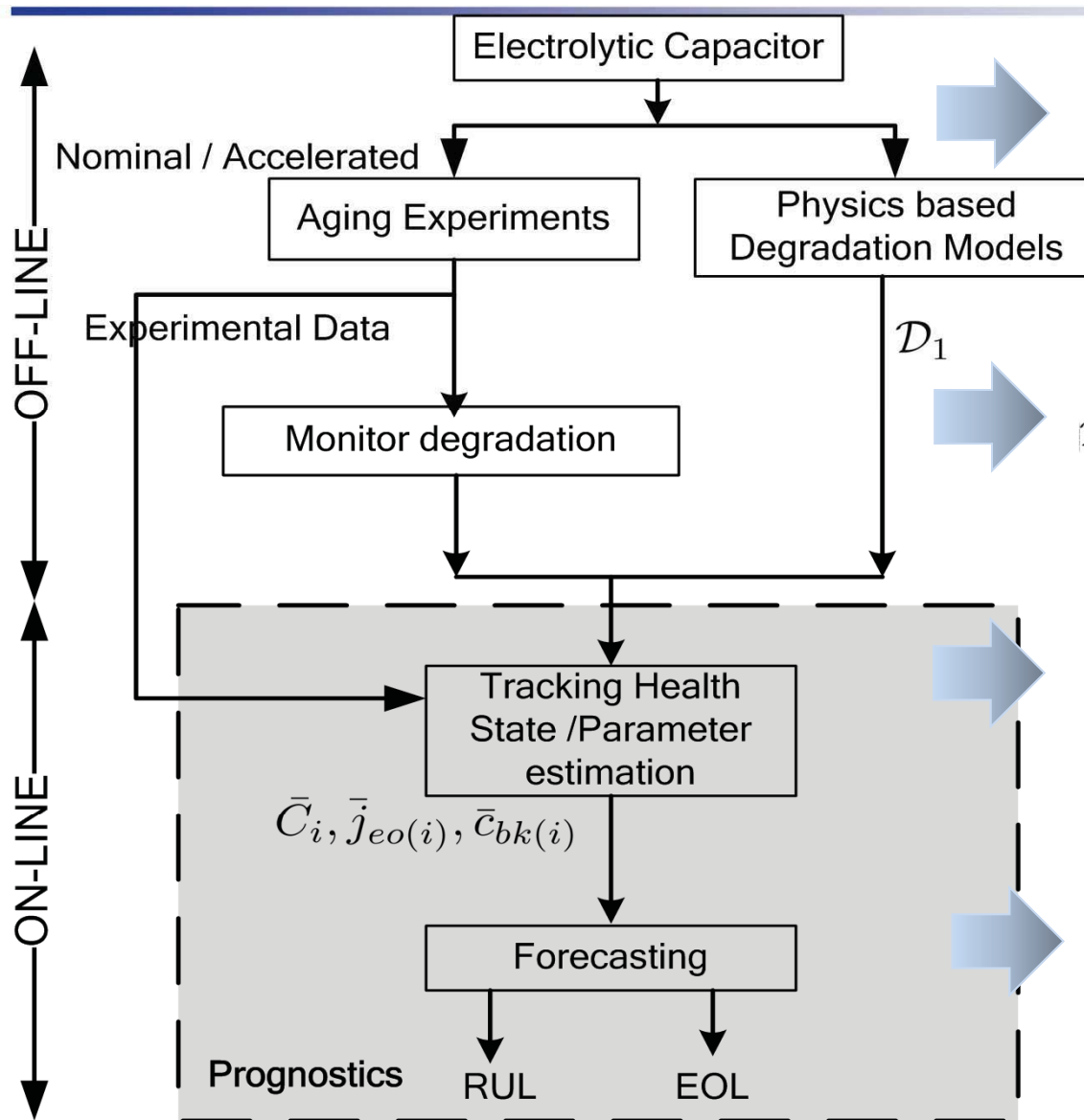
- Examples

- Particle Filters, Kalman Filters, etc.
- or any clever combination of different approaches...

Example 1

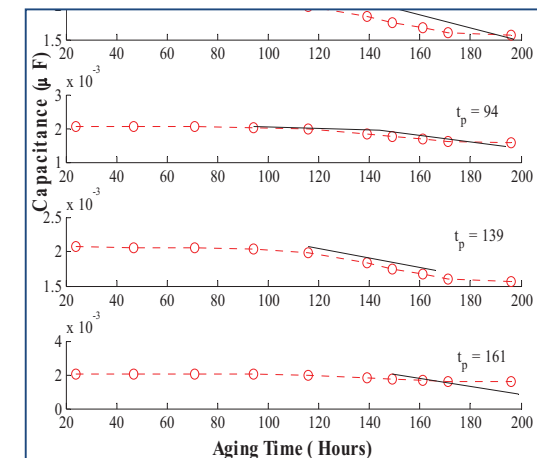
Electrolytic Capacitors

Research Approach



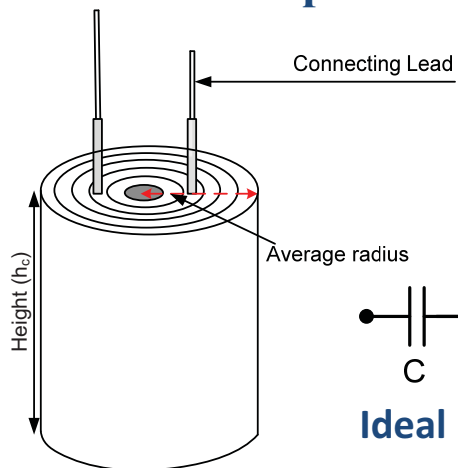
$$\mathcal{D}_1 : C(t) = \left(\frac{2\epsilon_R \epsilon_0 c_{bk}}{d_C} \right) \left(\frac{V_0 - V_e(t)}{j_{eo} t w_e} \right)$$

$$\mathcal{D}_4 : C_{k+1} = C_k - \frac{(2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk})}{d_C^2} \Delta t$$

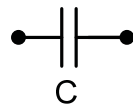


Capacitor Degradation Model

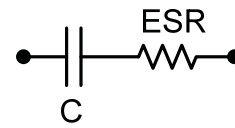
Pristine Capacitor



Electrolyte volume V_e maximum
Capacitance Value maximum



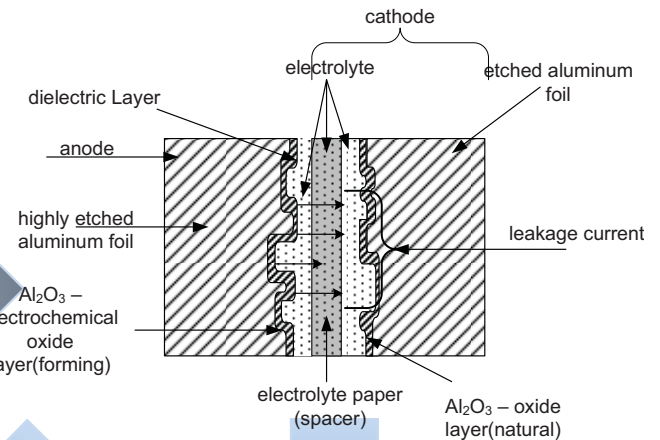
Ideal



Non-Ideal

\mathcal{M}_1

Degradation

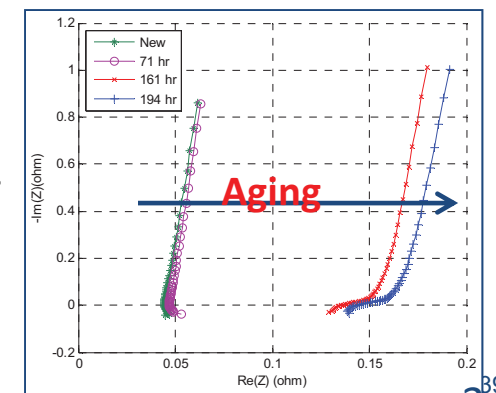
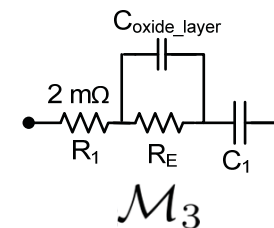
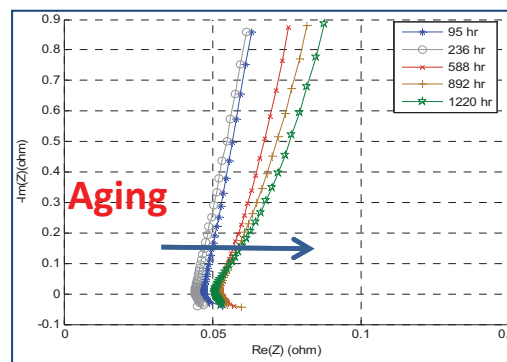
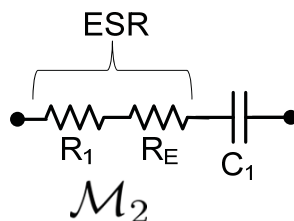


Thermal Stress

Electrical Stress

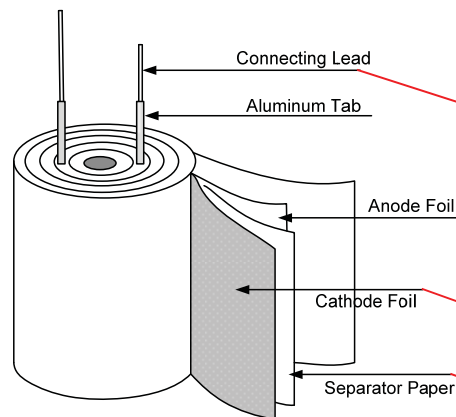
Avg. surface area decreases (A_s) + oxide layer breakdown

Electrolyte degradation + Decrease in (A_s) + crystallization + oxide layer breakdown

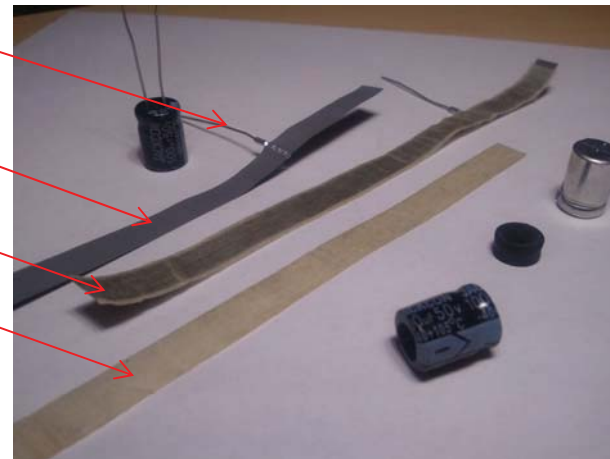


Capacitor Structure

- An aluminum electrolytic capacitor, consists of
 - Cathode aluminum foil,
 - Electrolytic paper, electrolyte
 - Aluminum oxide layer on the anode foil surface, which acts as the dielectric.
 - Equivalent series resistance (ESR) and capacitance(C) are electrical parameters that define capacitor health

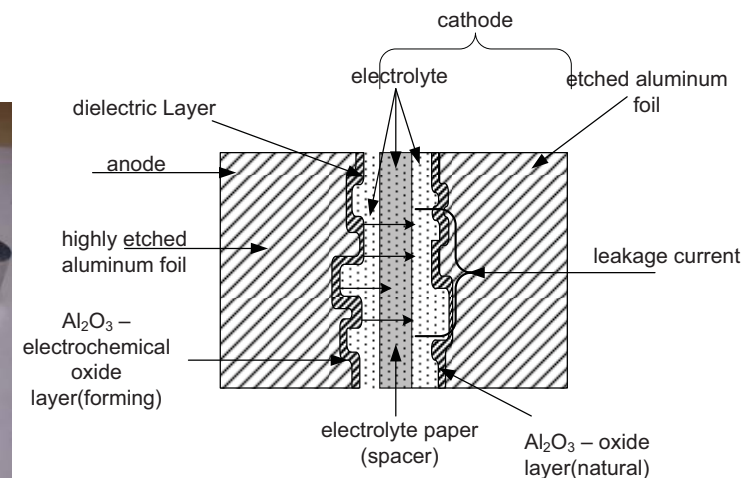


Physical Structure



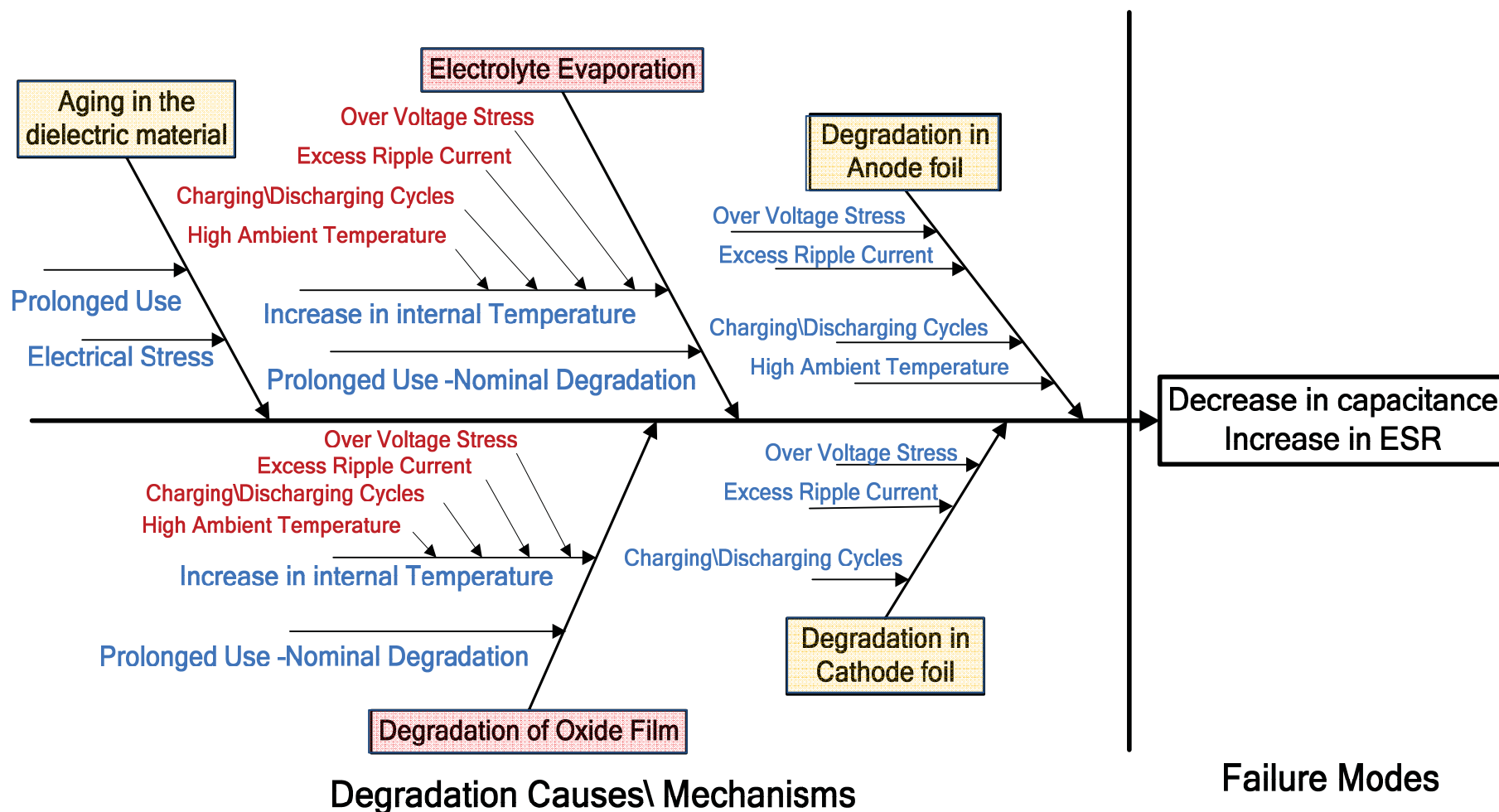
Ref
: <http://en.wikipedia.org/wiki/File:ElectrolyticCapacitorDisassembled.jpg>

Open Structure



Internal Structure

Degradation Mechanisms



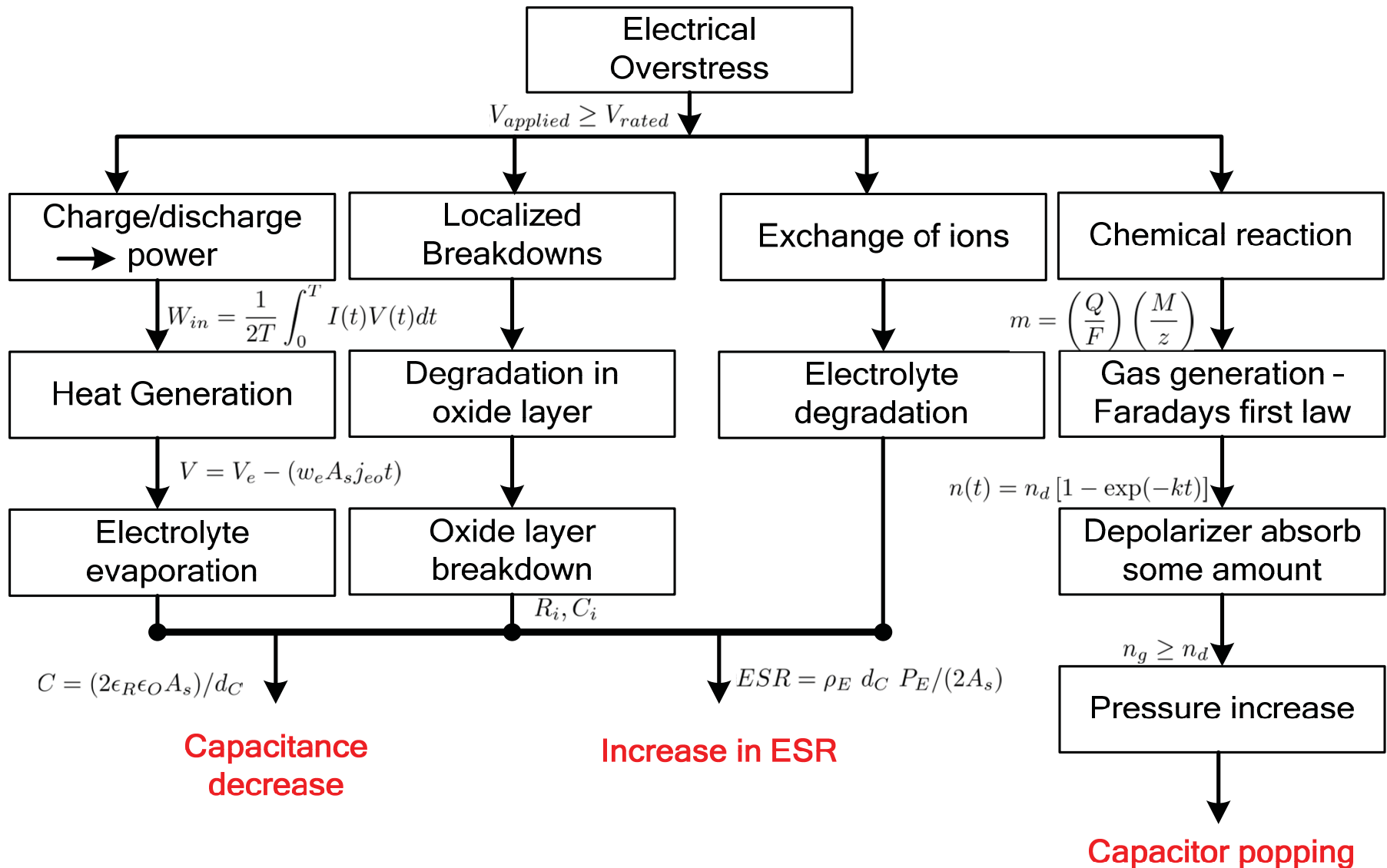
Experimental Setups

- Conditions under investigation
 - Nominal Degradation
 - Electrical Over Stress
 - Thermal Over Stress
- Characterization of capacitors at regular intervals
- Impedance measurement instrument used to characterize the capacitors.
- ESR and Capacitance values are computed using a system identification tool.

Accelerated Aging Studies

- Under normal operating conditions
 - Device lasts for several years
 - Process of condition based monitoring becomes difficult
- Advantage of accelerated stressors
 - We can run the component to failure
 - Allows for the understanding of the effects of failure mechanisms,
 - Identification of leading indicators of failure
 - The development of physics-based degradation models and RUL prediction

Accelerated Electrical Aging



Capacitance Degradation Model

- Decrease in electrolyte volume :

$$V_e(t) = V_{e0} - (w_e A_s j_{eo} t) \quad (1)$$

where:

V : dispersed volume at time t , V_e : initial electrolyte volume

A_s : surface area of evaporation, j_{eo} : evaporation rate

t : time in minutes, w_e = volume of ethyl glycol molecule

- Capacitance (C)): Physics-Based Model:

$$C = (2\epsilon_R \epsilon_O A_s) / d_C \quad (2)$$

- Electrolyte evaporation dominant degradation phenomenon

– First principles: Capacitance degradation as a function of electrolyte loss

$$\mathcal{D}_1 : C(t) = \left(\frac{2\epsilon_R \epsilon_0}{d_C} \right) \left(\frac{V_{e0} - V_e(t)}{j_{eo} t w_e} \right), \quad (3)$$

where:

C : capacitance of the capacitor,

ϵ_R : relative dielectric constant,

ϵ_O : permittivity of free space,

d_C : oxide thickness.

Capacitance Degradation Model

- Oxide breakdown observed - experimental data
- The breakdown factor is exp. function of electrolyte evaporation

$$C_{bk(t)} = \exp f(V_{eo} - V_{e(t)})$$

- Updated in capacitance degradation model :

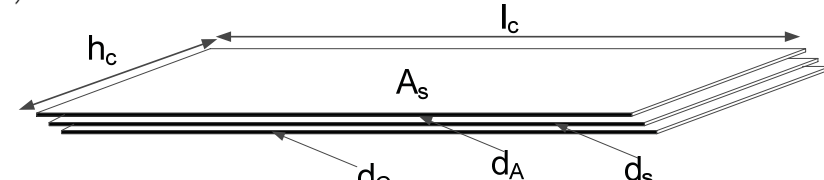
$$C = (2\epsilon_R\epsilon_0 A_s c_{bk}) / d_C,$$

$$\mathcal{D}_{11} : C(t) = c_{bk(t)} \left(\frac{2\epsilon_R\epsilon_0}{d_C} \right) \left(\frac{V_{eo} - V_e(t)}{j_{eo} t w_e} \right)$$

Dynamic Model of Capacitance

From the structure of capacitor we have the electrolyte volume(V_e) expressed in the form of oxide surface area (A_s) as :

$$V_e = A_s \cdot d_C, \quad (4)$$

$$A_s = \frac{V_e}{d_C}.$$


The first order discrete approximation for change in electrolyte volume can be expressed as:

$$\frac{dV_e}{dt} = -(w_e A_s j_{eo}), \quad (5)$$

$$V_{e(k+1)} = V_{e(k)} + \frac{dV_e}{dt} \Delta t,$$

$$V_{e(k+1)} = V_{e(k)} - (w_e A_s j_{eo}) \Delta t.$$

Dynamic Model of Capacitance

$$\begin{aligned}
 V_{e(k)} &= \frac{C_k}{2\epsilon_R\epsilon_0 c_{bk}} d_C^2, \\
 V_{e(k)} &= (C_k)\alpha
 \end{aligned} \tag{6}$$

Similarly Capacitance can be expressed as :

$$\begin{aligned}
 C_{k+1}\alpha &= C_k\alpha + \frac{dV_e}{dt}\Delta t, \\
 C_{k+1}\alpha &= C_k\alpha - (w_e A_s j_{eo})\Delta t, \text{ hence} \\
 C_{k+1} &= C_k - \frac{(w_e A_s j_{eo})}{\alpha} \Delta t.
 \end{aligned} \tag{7}$$

The complete discrete time dynamic model for capacitance degradation can be summarized as :

$$\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R\epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2} \right) \Delta t$$

Dynamic Model of ESR

- Decrease in electrolyte volume :

$$V_e(t) = V_{e0} - (w_e A_s j_{eo} t)$$

- ESR

- Based on mechanical structure and electrochemistry.
- With changes in R_E (electrolyte resistance)

$$ESR = \frac{1}{2} \left(\frac{\rho_E d_C P_E e_{bk}(t)}{A_s} \right) \quad (8)$$

$$\mathcal{D}_2 : ESR(t) = \frac{1}{2} (\rho_E d_C P_E) \left(\frac{j_{eo} t w_e e_{bk}(t)}{V_e(t)} \right)$$

Dynamic ESR degradation Model :

$$\mathcal{D}_5 : \frac{1}{ESR_{k+1}} = \frac{1}{ESR_k} - \left(\frac{2w_e A_s j_{eo}}{\rho_E P_E d_C^2 e_{bk}(t)} \right) \Delta t$$

where:

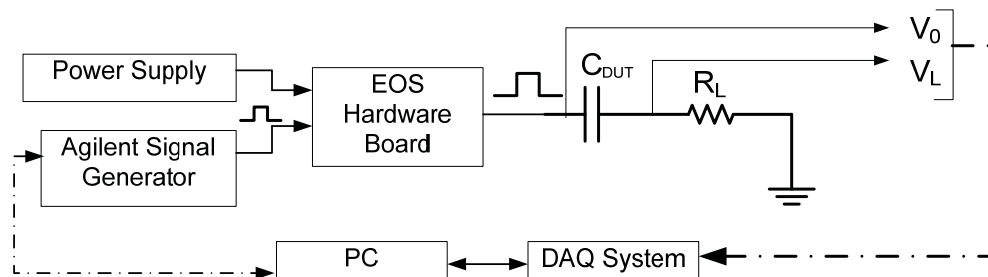
ρ_E : electrolyte resistivity,

P_E : correlation factor related to electrolyte spacer porosity and average liquid pathway,

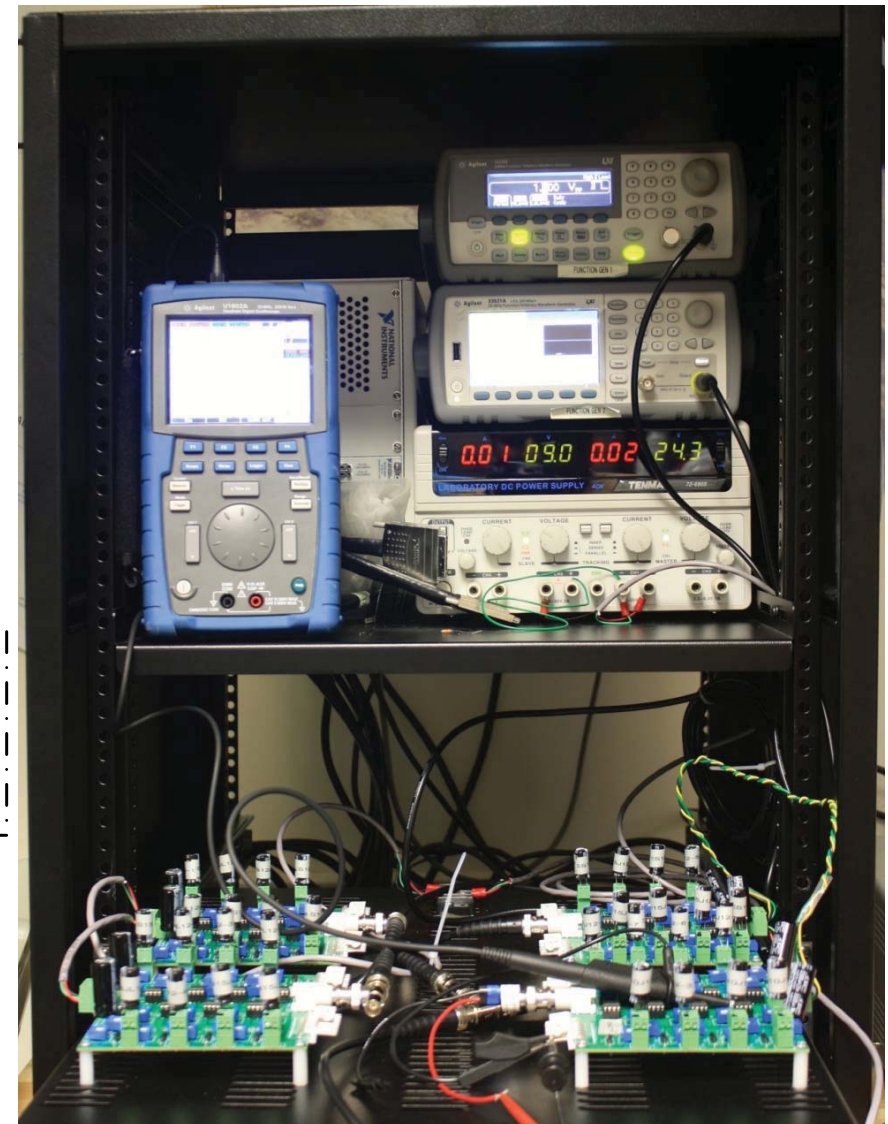
$e_{bk}(t)$: resistance dependence oxide breakdown factor

Electrical Overstress Experiment

- Electrolytic capacitors of $2200\mu\text{F}$, 10V, 1A and at 85°C
- Stress voltages
 - 120% , 150% of rated voltage
- Under Electrical Overstress
 - Capacitance Health Threshold – 20%
 - ESR Health Threshold – 250 – 280%
- Charging / discharging cycle – 15V

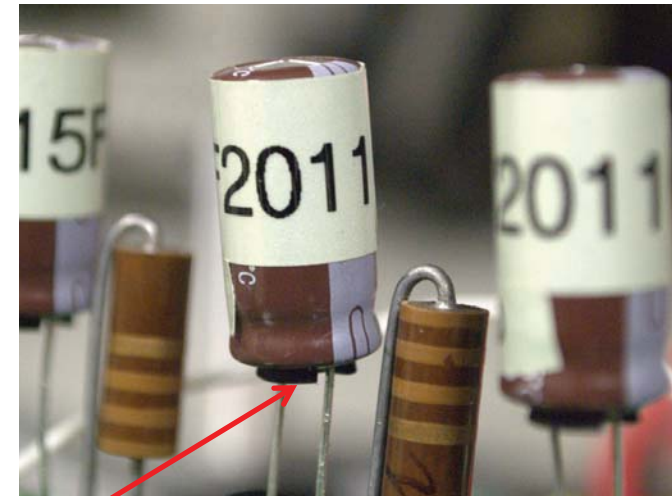
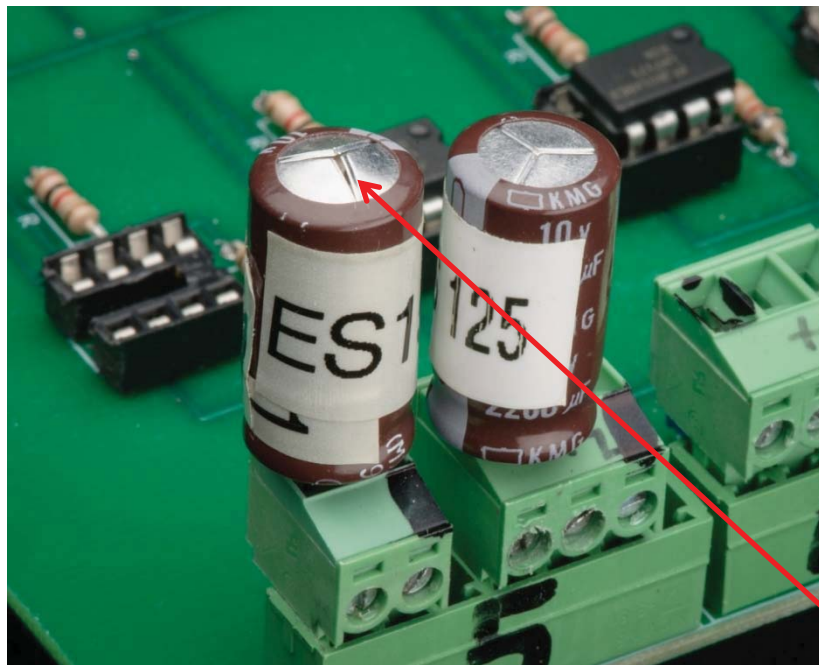


For this experiment ESR (> 55%)
and capacitance decrease (> 22-
24%)

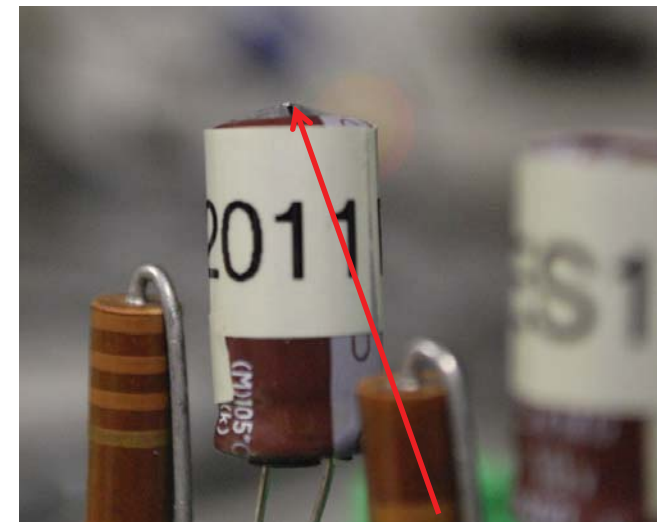


Electrical Overstress Experiment

- EOS Experiments :
 - 3 Capacitors failed due to vent opening.
 - Pressure increase in other devices observed.



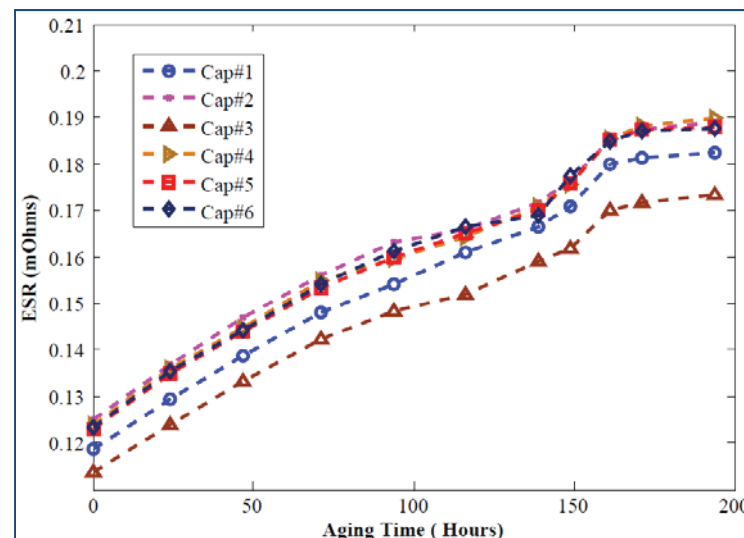
Increase in pressure



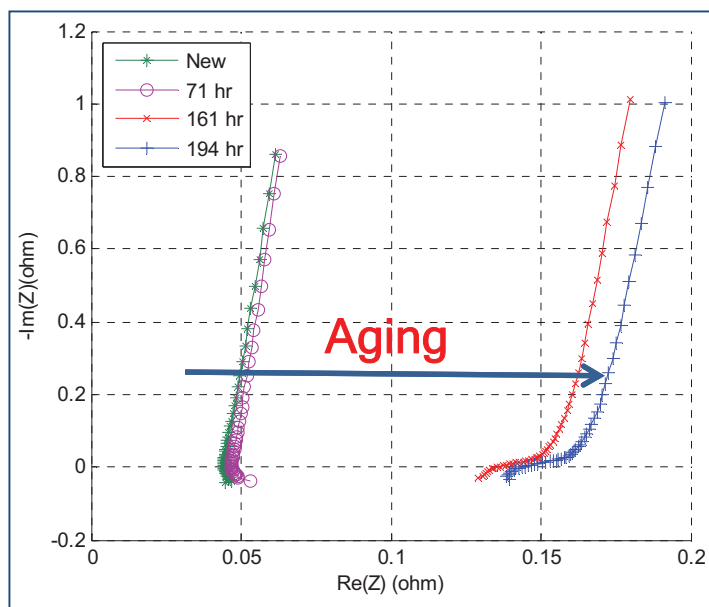
Opening of the pressure vent

Electrical Overstress Degradation Data

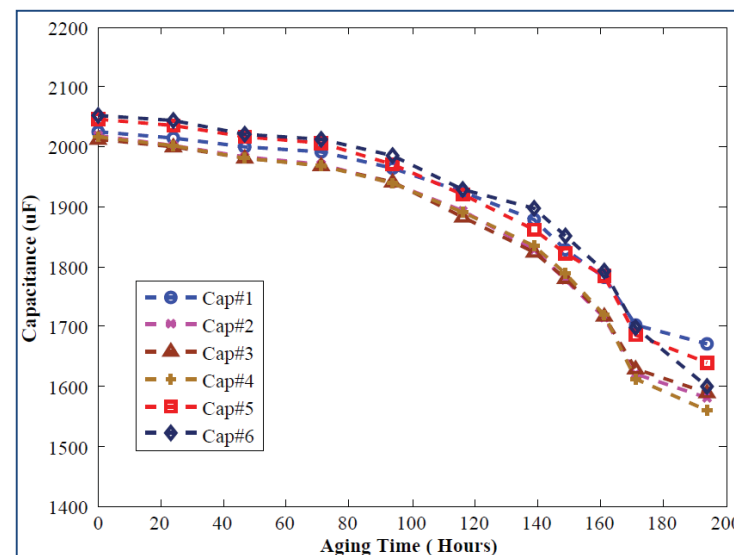
- Devices were characterized at regular intervals.
- Impedance data shows degradation in C and ESR with aging
- C and ESR values were computed from the impedance data



ESR Increase



Nyquist Impedance Plots

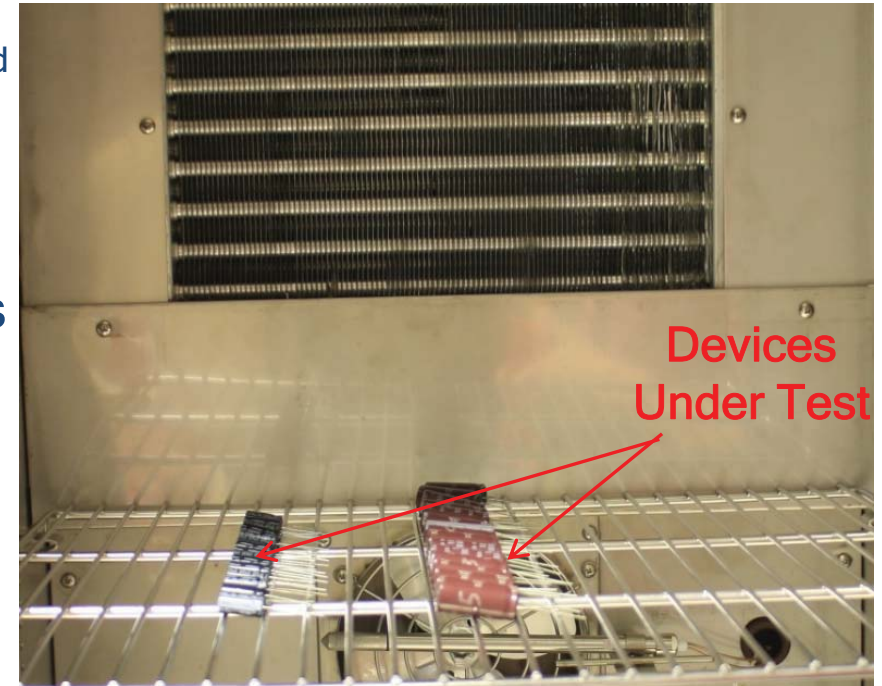


Capacitance Decrease

Thermal Overstress Experiment

Thermal Chamber

- Exposure of the capacitors to temperatures $T_{\text{applied}} (105^\circ\text{C}) \geq T_{\text{rated}} (85^\circ\text{C})$ results in accelerated aging of the devices
- High temperature on the surface causes heat to flow radially towards the core of the capacitor
- Temperature increase leads to electrolyte evaporation
- Health Threshold Storage condition - capacitance decreases $> 10\%$
- Oxide breakdown observed



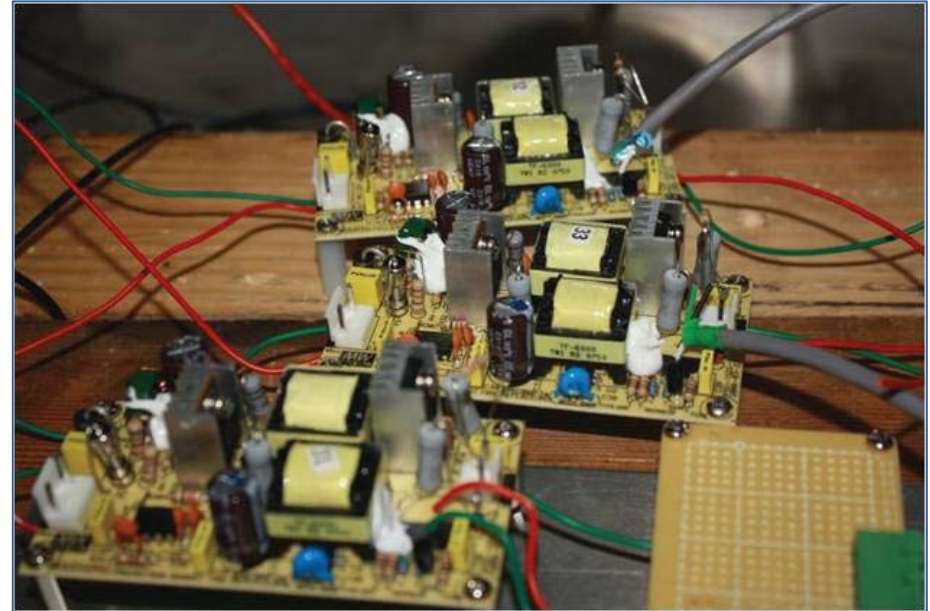
		15 min	T_{applied}
1	2200uF, 10V, 85°C	$\xrightarrow{+25^\circ\text{C}}$	$105^\circ\text{C} - 3400 \text{ hrs}$
2	10,000uF, 15V, 85°C	$\xrightarrow{+25^\circ\text{C}}$	$105^\circ\text{C} - 3400 \text{ hrs}$

$T_{\text{RT}} \xrightarrow{+25^\circ\text{C}}$

Capacitance decrease ($> 15 - 17\%$)
Linear decrease till 2800 hrs

Nominal Operation Experiment

- Three sets of DC-DC converters with electrolytic capacitors under test
- Main components include MOSFET's, isolating transformers, PWM controller chip and an **electrolytic capacitor**
- Characterization of capacitors done at regular time intervals.
 - Voltage source shut down, capacitors discharged
 - Experiment was started with conditions intact again till the next measurement

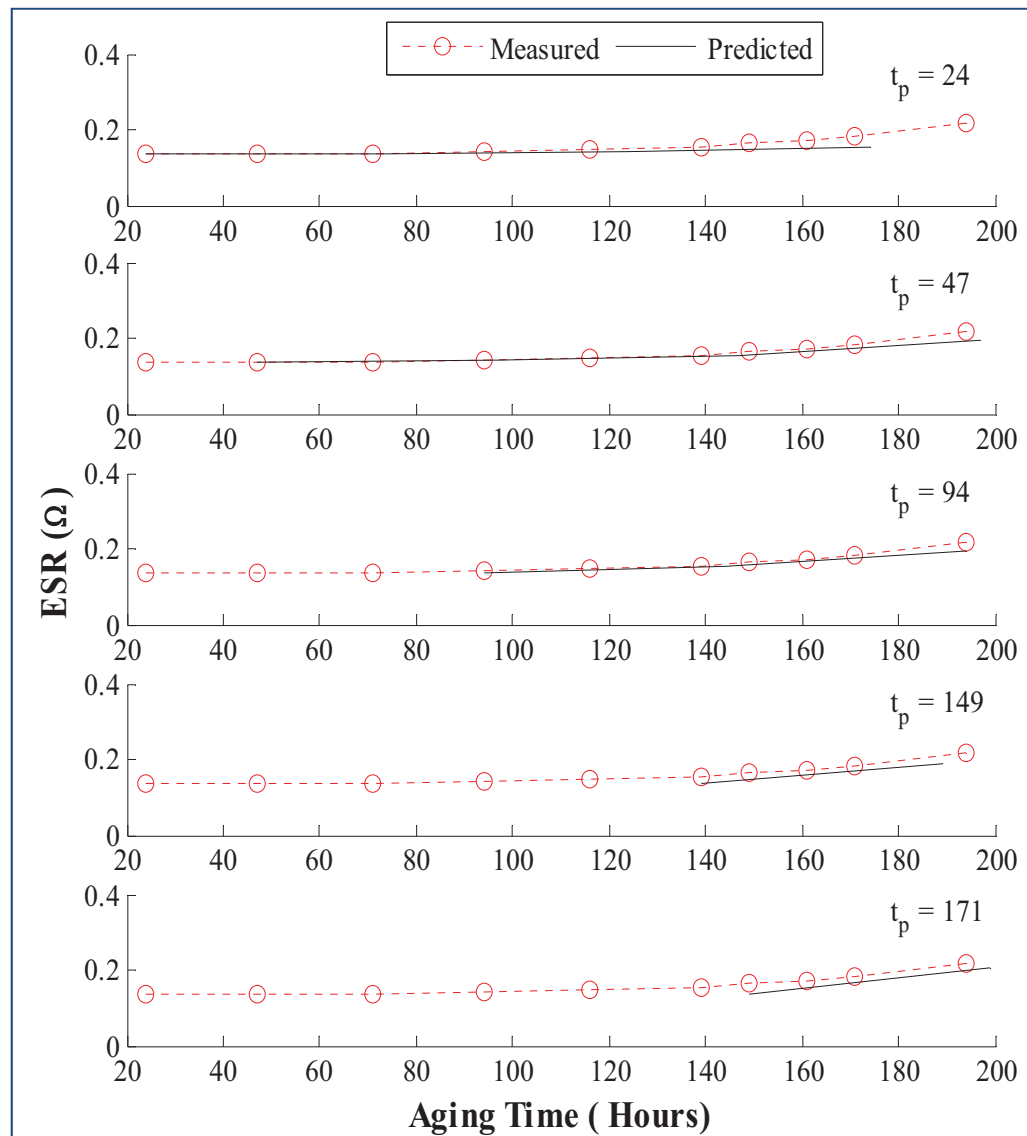
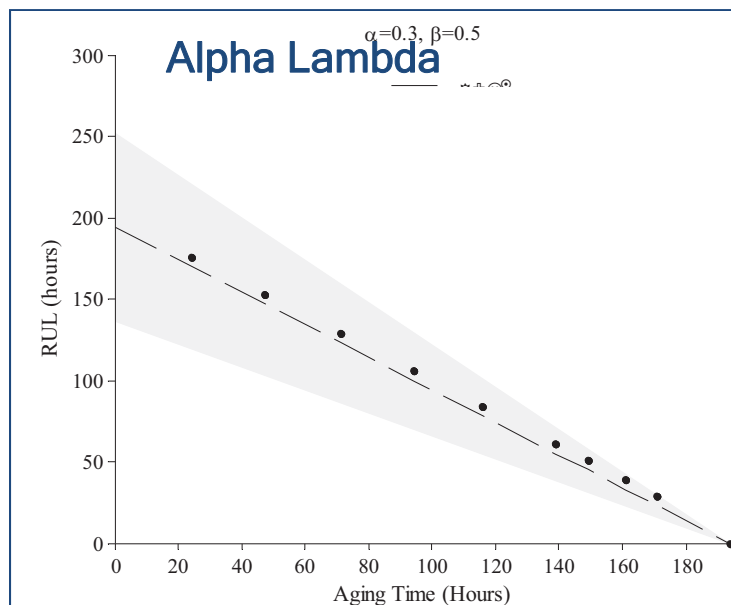
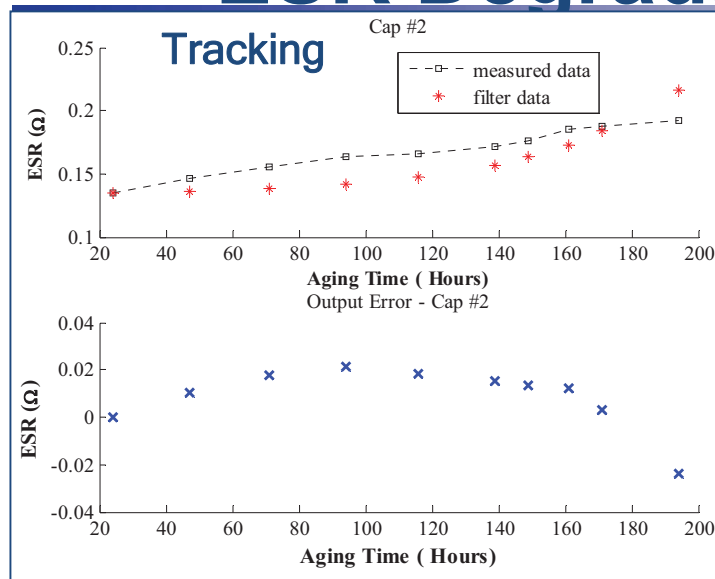


For this experiment ESR increase ($> 103\%$) and capacitance decrease ($> 8\%$)

RUL and Validation – EOS -Experiment – ESR Degradation Model



D_5



Predictions at different aging time

Summary of RUL forecasting results TOS



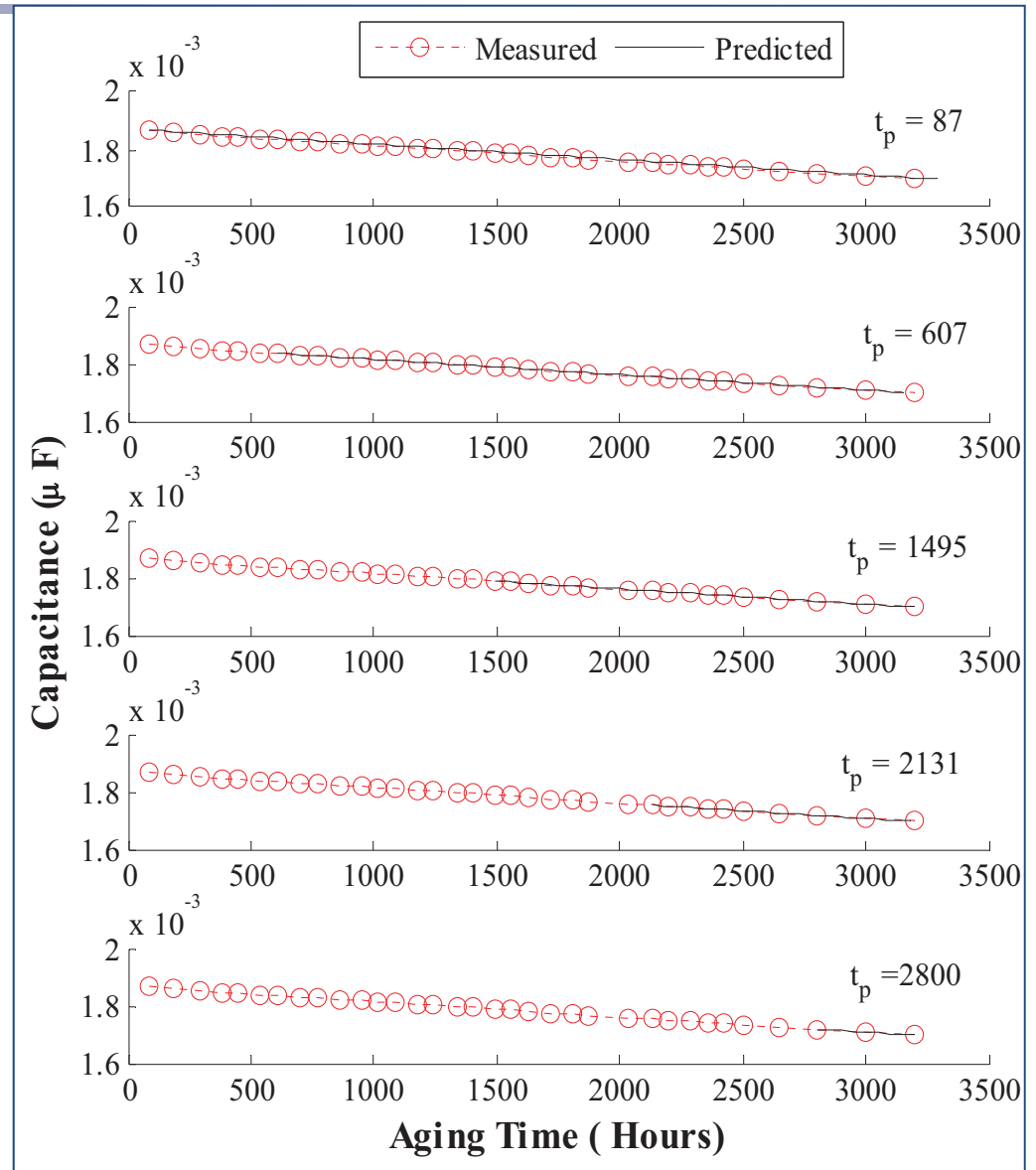
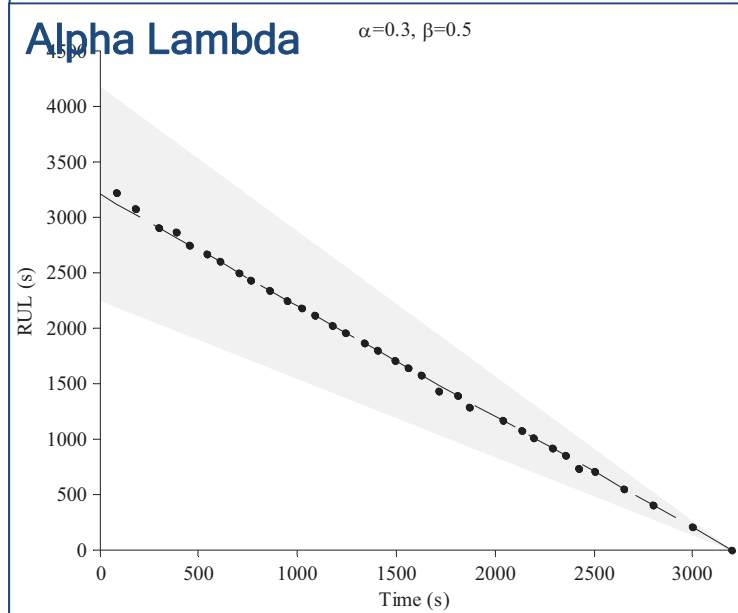
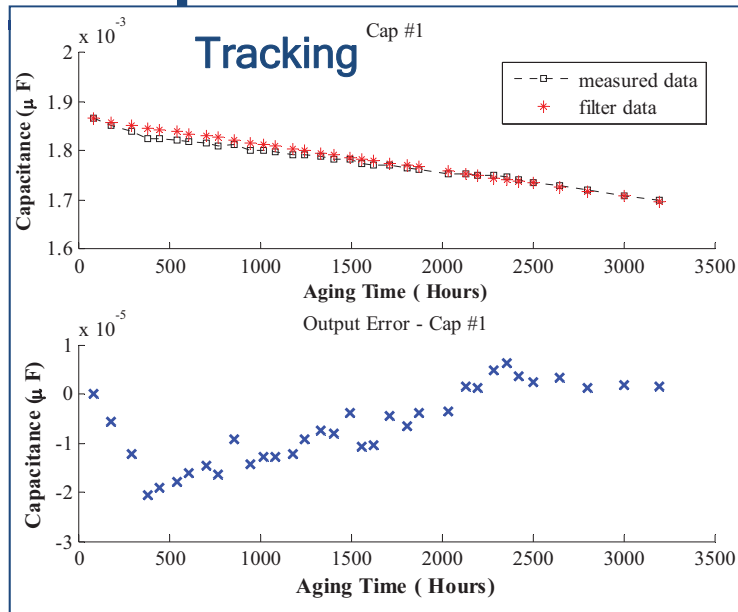
~~Experiments~~

- 2200 μ F capacitors at 105°C
- Capacitance Degradation Model

\mathcal{D}_4

Aging Time	Evaporation Rate (j_{eo})	Evap. Rate and Oxide Breakdown
	\overline{RA}_{a1}	\overline{RA}_{a2}
2421.92	90.15	94.47
2500	85.71	97.86
2650	78.18	94.76
2800	65.00	95.15
3000	43.18	95.00
\overline{RA}_b	92.32	93.52

RUL and Validation – TOS -Experiment - Capacitance



Predictions at different aging time

Example 2

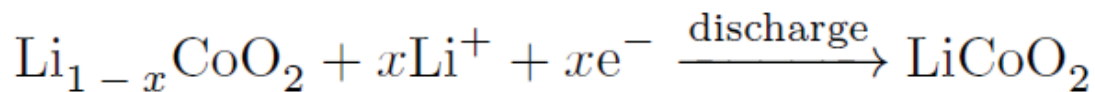
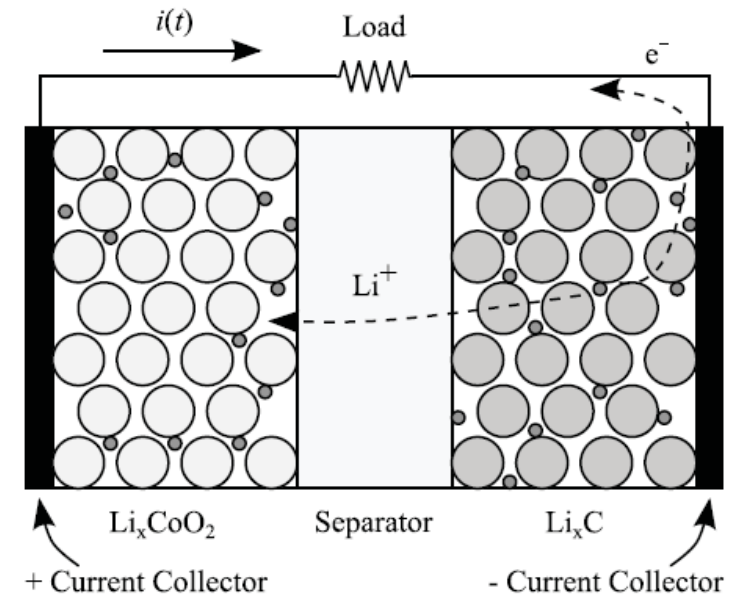
Li-Ion Batteries

Background

- For Li-ion, a common chemistry
 - positive electrode consisting of lithium cobalt oxide (Li_xCoO_2)
 - negative electrode of lithiated carbon (Li_xC).
- Electrolyte enables lithium ions (Li^+) to diffuse between the positive and negative electrodes.
- Intercalation/charging and deintercalation/discharging process

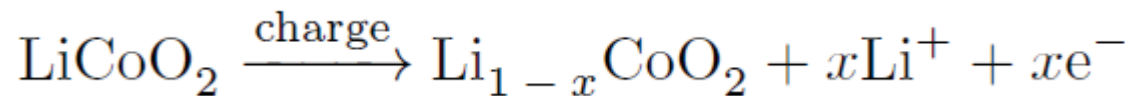
Background - Discharging

- On connecting to load
 - current flow leads to oxidation reaction
- $$\text{Li}_x\text{C} \xrightarrow{\text{discharge}} \text{C} + x\text{Li}^+ + xe^-$$
- liberation of Li ions and electrons
 - positive electrode the reduction reaction takes place

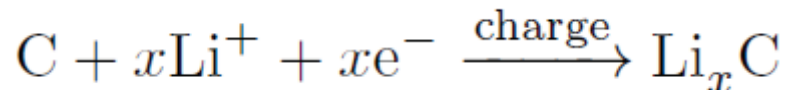
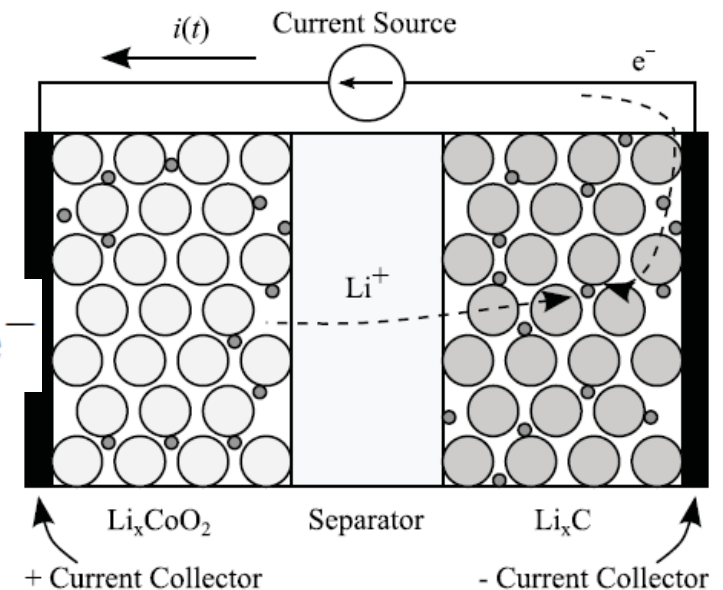


Background - Charging

- During charging
 - active material in the positive electrode (anode) is oxidized and Li ions are de-intercalated



- results in the loss of Li ions and electrons, which can then move to the negative electrode (cathode).



Aging Process

- Solid-electrolyte interface (SEI) layer
 - degradation in the negative electrode
 - increase in impedance
- Lithium corrosion
 - degradation with aging
 - decrease in capacity.
- Lithium plating
 - irreversible loss due to plating formation
- Contact Loss
 - SEI layer disconnects from the negative electrode, impedance increase

Problem Formulation

- Prognostics goal
 - Compute EOL = time point at which component no longer meets specified performance criteria
 - Compute RUL = time remaining until EOL

- System model

$$\begin{aligned}
 \dot{\mathbf{x}}(t) &= \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t)) \\
 \text{Output } \mathbf{y}(t) &= \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t))
 \end{aligned}$$

State Parameters Input Process Noise
 Output Sensor Noise

- Define threshold that determines if EOL has been reached

$$T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = \begin{cases} 1, & \text{if EOL is reached} \\ 0, & \text{otherwise.} \end{cases}$$

- EOL and RUL defined as

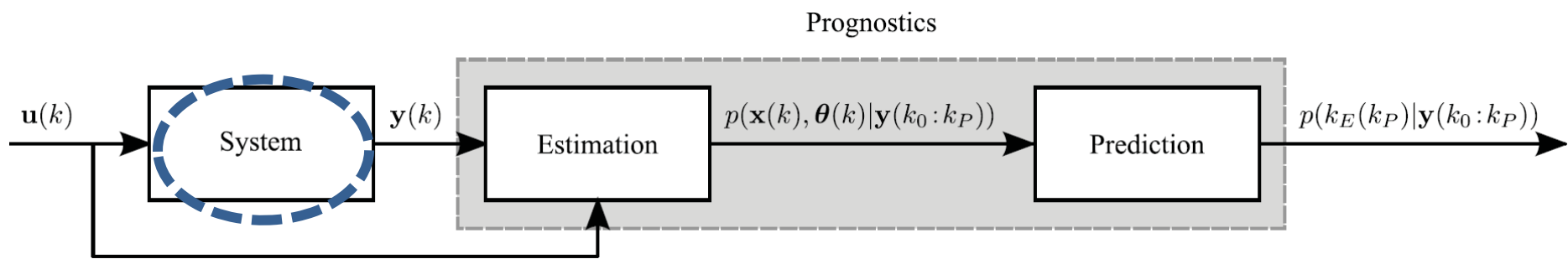
$$EOL(t_P) \triangleq \arg \min_{t \geq t_P} T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 1 \quad RUL(t_P) \triangleq EOL(t_P) - t_P$$

Compute $p(EOL(t_P) | \mathbf{y}_{0:t_P})$ and/or $p(RUL(t_P) | \mathbf{y}_{0:t_P})$

Prognostics Architecture

1

System receives inputs, produces outputs



2

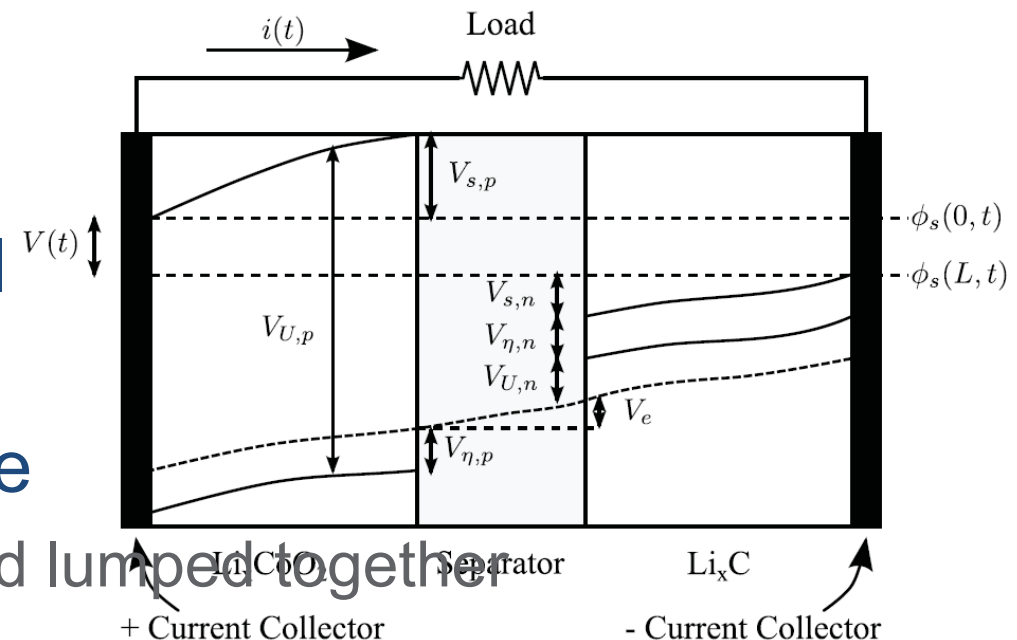
Estimate current state and parameter values

3

Predict EOL and RUL as probability distributions

Battery Modeling

- Overall Battery Voltage
 - potential at positive current collector
 - potential Negative current collector
 - resistance losses
- Equilibrium potential
 - Nernst Equation
- Surface over-potential
 - Butler-Volmer
- Solid-phase resistance
 - treated as constant and lumped together



Battery Voltage

- The total battery voltage can be given as :

$$V = V_{U,p} - V_{U,n} - V_o - V_{\eta,p} - V_{\eta,n}.$$

- Change in voltage levels and transients

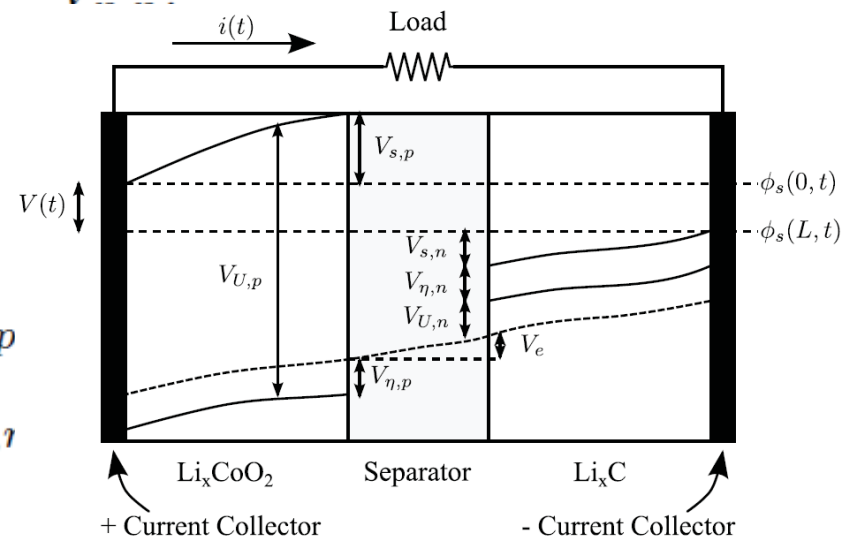
$$V = V_{U,p} - V_{U,n} - V_o' - V_{\eta,p}' - V_{\eta,n}'$$

where

$$\dot{V}_o' = (V_o - V_o')/\tau_o$$

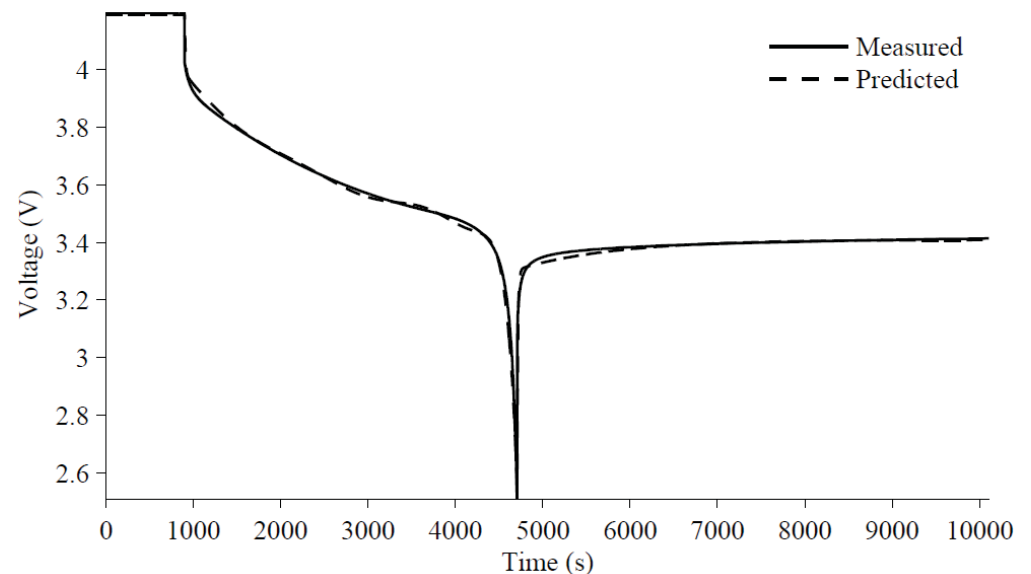
$$\dot{V}_{\eta,p}' = (V_{\eta,p} - V_{\eta,p}')/\tau_{\eta,p}$$

$$\dot{V}_{\eta,n}' = (V_{\eta,n} - V_{\eta,n}')/\tau_{\eta,n}$$



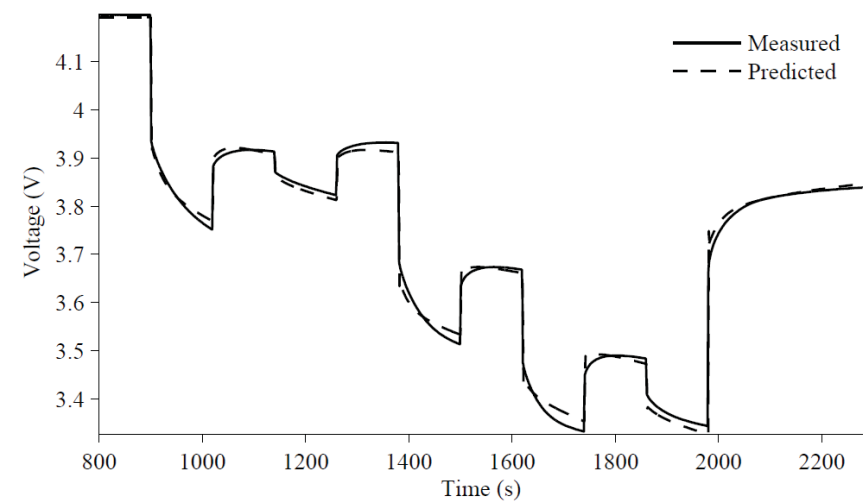
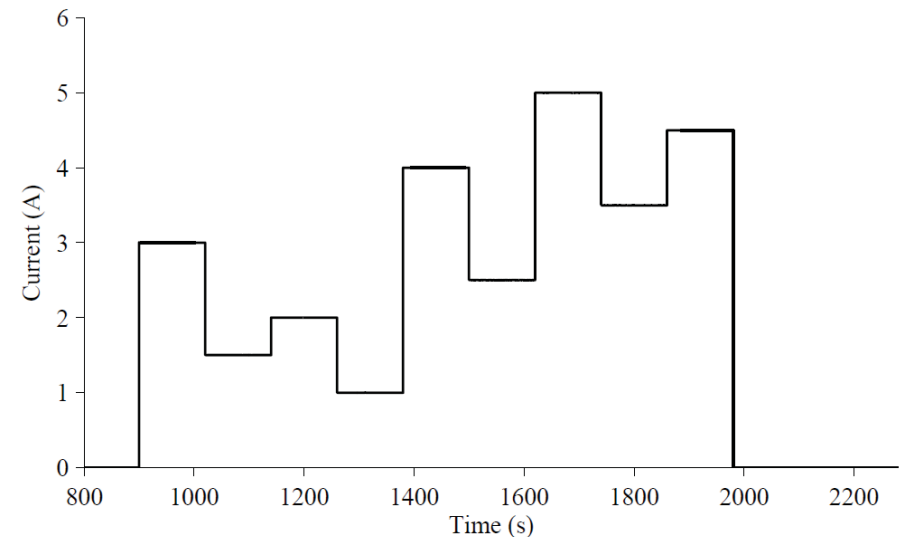
Constant 2A discharge

- Model fits very well
- The accuracy towards the end of discharge is most sensitive to the
 - Redlich-Kister parameters
 - Diffusion constant
 - Volume of surface layer



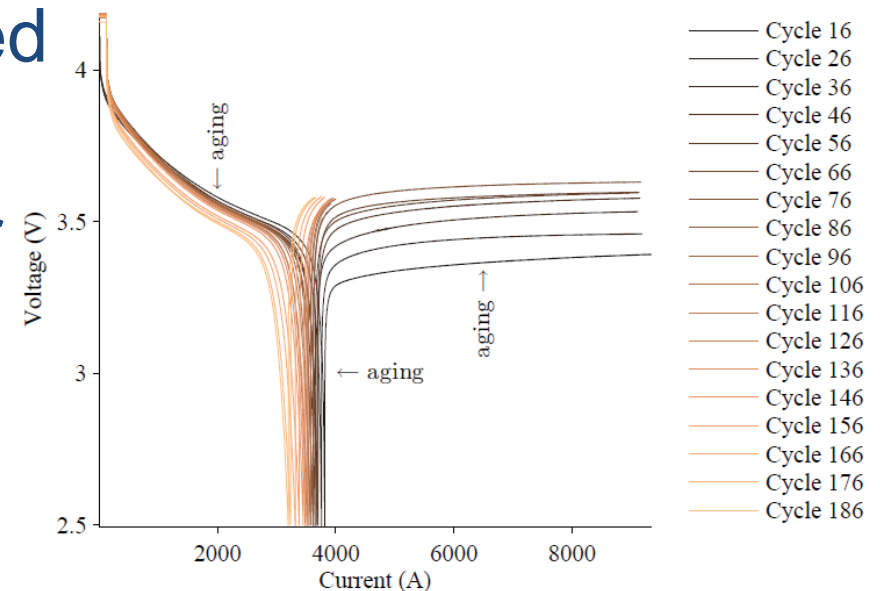
Variable Loading

- Load changes every 2 mins
- Results in corresponding changes in voltage
- Predictions are fairly accurate
- Some errors still present possibly accounted by thermal effects



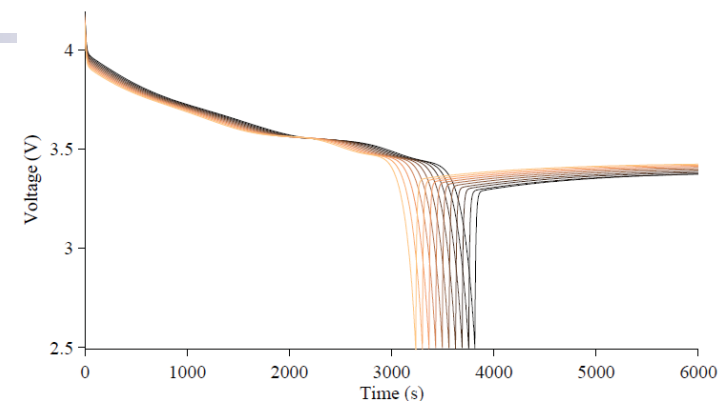
Battery Aging - Experiments

- EOD point moves earlier in time due to diminished capacity.
- Voltage drops down during discharge due to increased resistance
- Steady-state voltage after discharge increases

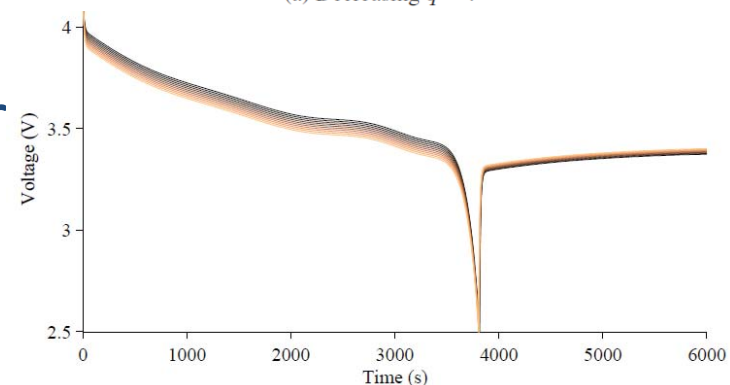


Battery Aging Model

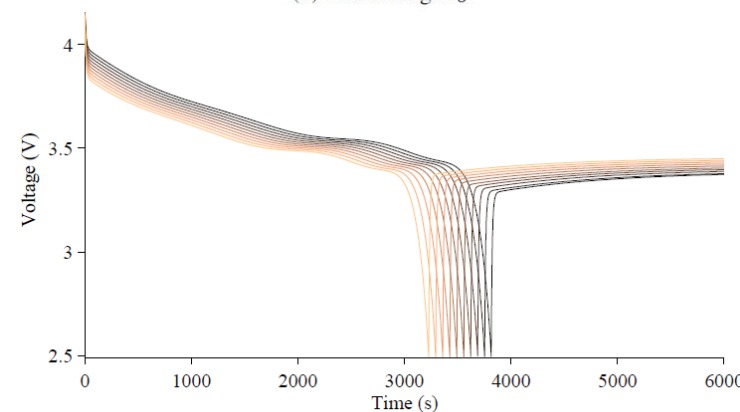
- Total available charge in the battery is represented through q^{\max}
- Loss of active material
- Decrease in voltage due to Butler Volmer term
- Increase in internal resistance captured through an increase in the R_o parameter



(a) Decreasing q^{\max} .



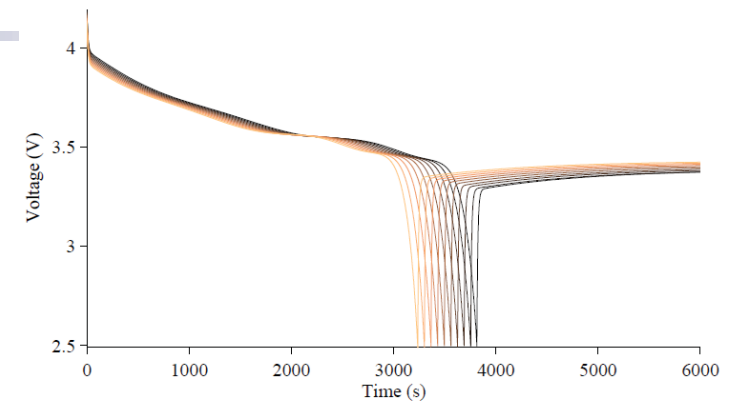
(b) Decreasing R_o .



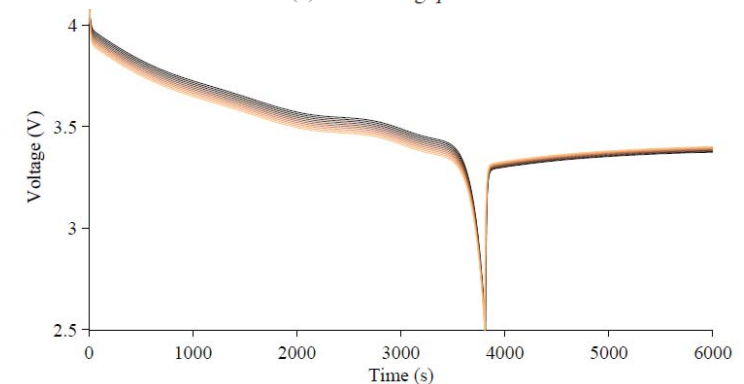
(c) Decreasing q^{\max} and R_o .

Battery Aging Model

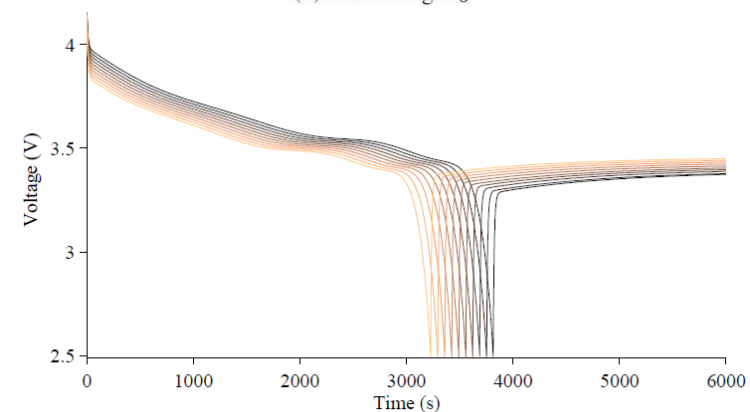
- Dynamics near EOD are dominated mainly by the equilibrium potential contribution with some contribution from the Butler-Volmer dynamics
- combined effects, with q_{\max} decreasing by 1% and R_o increasing by 5% with each new discharge.
- Similar to observed in experimental data



(a) Decreasing q^{\max} .



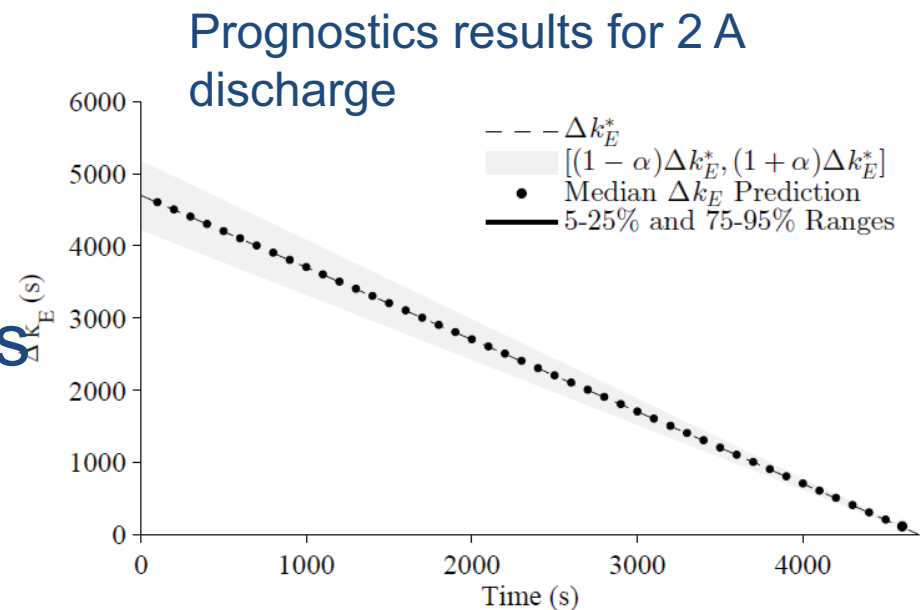
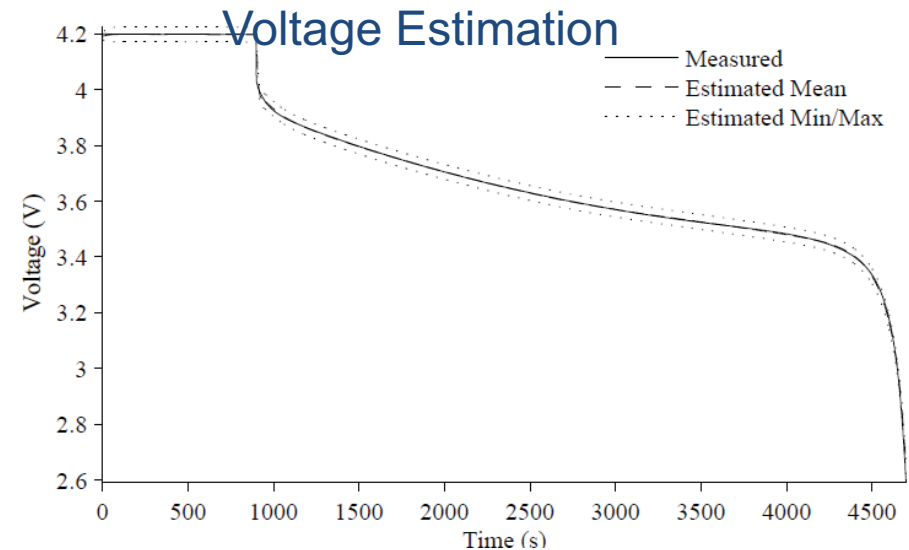
(b) Decreasing R_o .



(c) Decreasing q^{\max} and R_o .

Prognostics Performance

- UKF is used for state estimation
- Each sigma point is simulated forward using the model until EOD is reached
- We assume future loading points
- Model tracks very well under different conditions



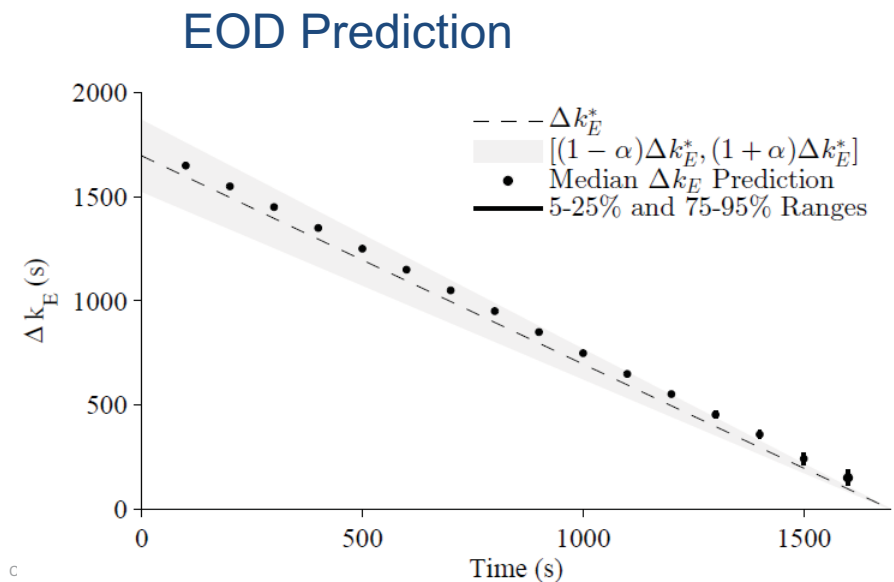
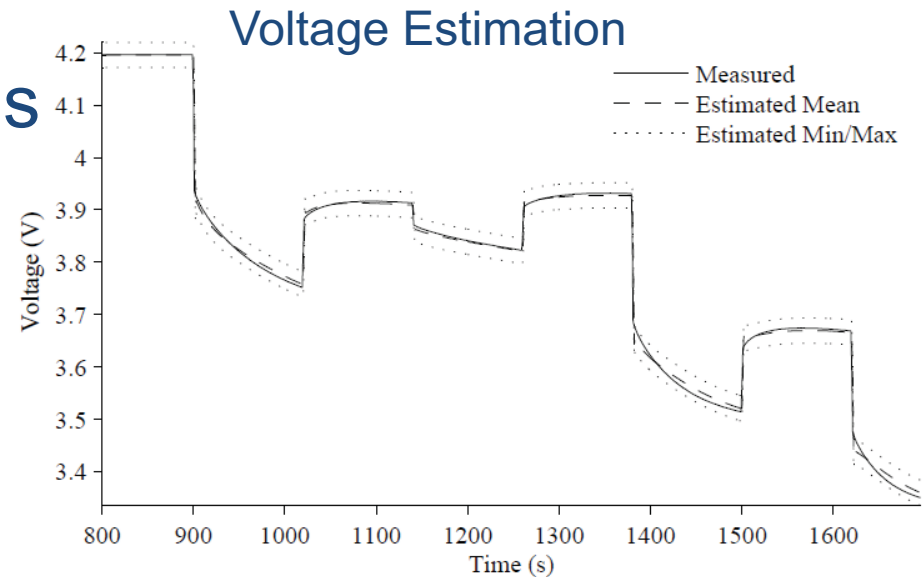
Prognostics Performance

- Each sigma point is simulated forward using the model until EOD is reached
- We assume future loading points are known
- Model tracks very well under different conditions

i_{app}	PRMSE	RA	RMAD _{RUL}
1.0	0.19	92.77	1.07
1.5	0.17	96.02	0.88
2.0	0.17	99.38	0.75
2.5	0.26	97.75	0.82
3.0	0.41	96.08	0.92

Prognostics Performance

- EOD being defined in this case as 3:35 V.
- In the open loop, the model slightly overestimates EOD
- Model tracks very well under different conditions
- RA averages 88:41%



Conclusions

- Discussed the lumped parameter electrical equivalent models
 - Study the links between the equivalent models and different degradation conditions.
- Stressors leading to degradation in capacitors are electrical and thermal overstress conditions respectively
- Developed appropriate experimental setups,
 - conducted laboratory experiments
 - Simulating capacitors under different operating conditions.
- Development of generalized physics based degradation models for C and ESR
 - Structural and manufacturing data
 - First principles of operation
 - Experimental Data

Discussion

- Electrochemistry based model discussed
- Prognostics results for EOD predictions are accurate
- The model can be applied to battery packs
- Two approaches
- Either each battery modeled individually
- Battery pack lumped to a single cell

Acknowledgements

Member of the Prognostics Center of Excellence (PCoE) at Ames Research Center

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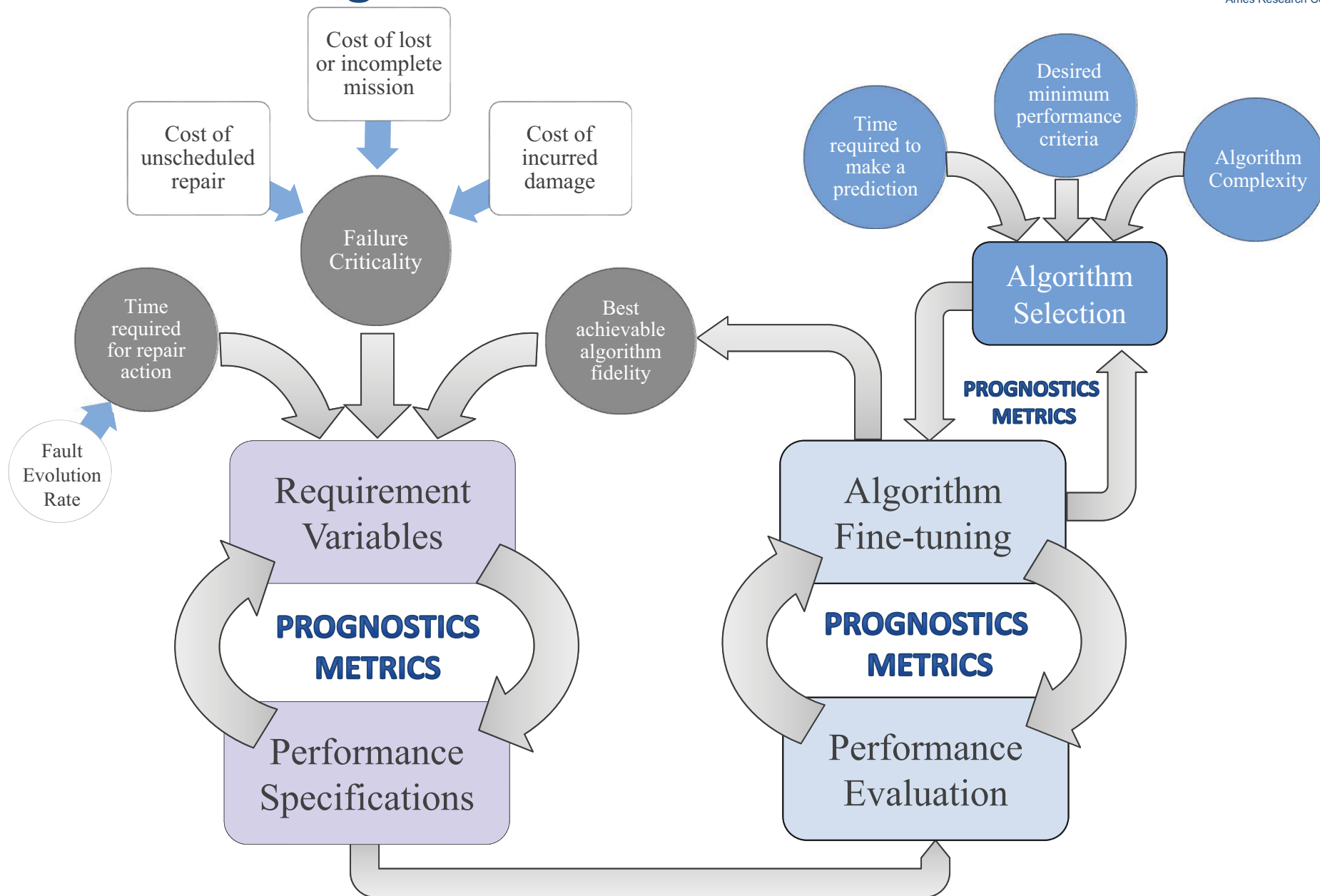
<http://prognostics.nasa.gov>

THANK YOU !!!

Prognostic Performance Evaluation

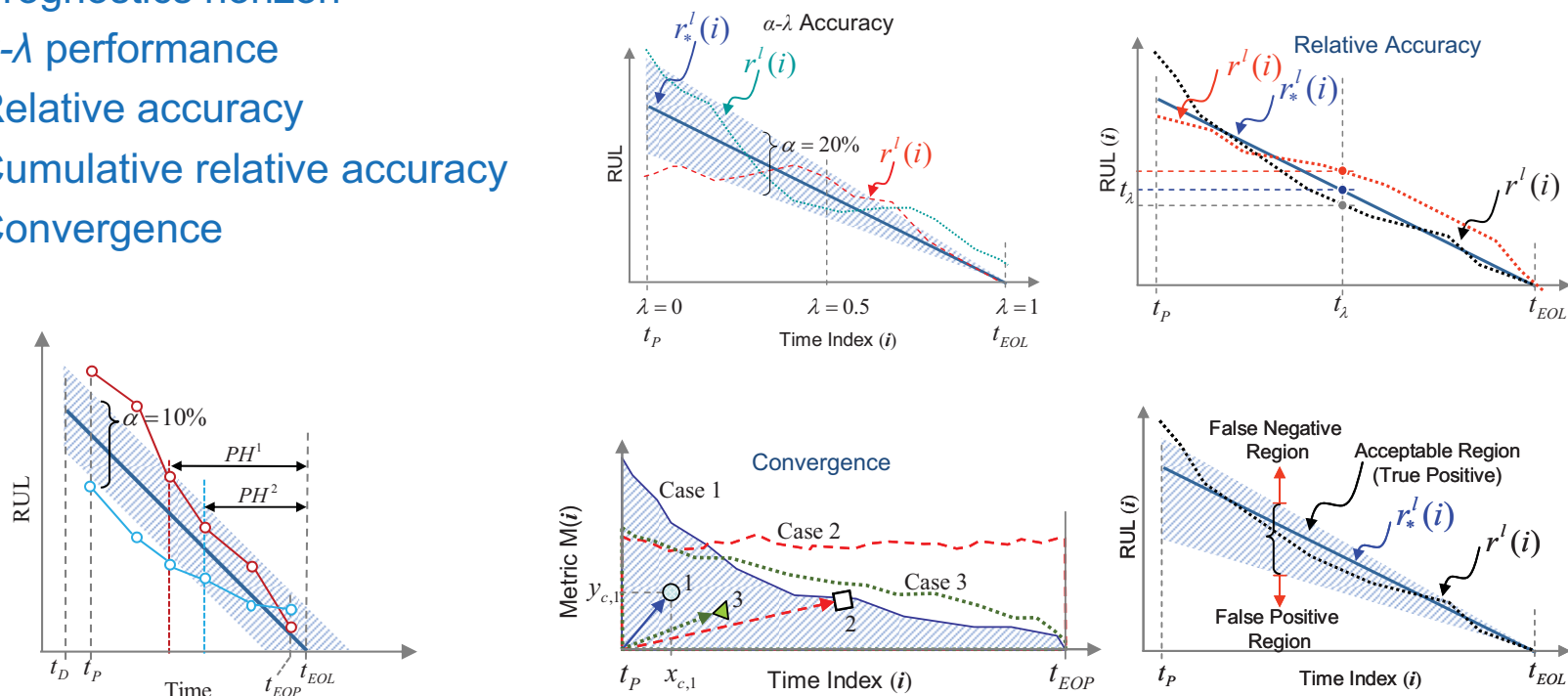
Prognostics Metrics

Role of Prognostics Metrics



Prognostic Performance Metrics

- New metrics were proposed specific to prognostics for PHM
- These metrics were applied to
 - A combination of different algorithms and different datasets
- Metrics were evaluated and refined
- Prognostics horizon
- α - λ performance
- Relative accuracy
- Cumulative relative accuracy
- Convergence



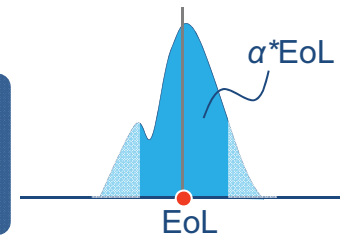
Source: A. Saxena, J. Celaya, E. Balaban, K. Goebel, B. Saha, S. Saha, and M. Schwabacher (2008). *Metrics for evaluating performance of prognostic techniques*. *International Conference on Prognostics and Health Management, PHM 2008*. 6-9 Oct. 2008 Page(s): 1-17.

Prognostic Performance Metrics

- Metrics Hierarchy

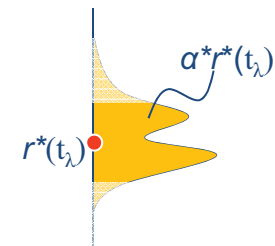
I. Prognostic Horizon

- Does the algorithm predict within desired accuracy around EoL and sufficiently in advance?



II. α - λ Performance

- Further does the algorithm stay within desired performance levels relative to RUL at a given time?



III. Relative Accuracy

- Quantify how well an algorithm does at a given time relative to RUL

IV. Convergence Rate

- If the performance converges (i.e. satisfies above metrics) quantify how fast does it converge

Prognostic Horizon (PH)

- Prognostic Horizon** is defined as the difference between the time index i when the predictions first meet the specified performance criteria (based on data accumulated until time index i) and the time index for End-of-Life (EoL). The performance specification may be specified in terms of allowable error bound (α) around true EoL.

$$PH = t_{EoL} - t_{i_{\alpha\beta}}$$

$i_{\alpha\beta}$ is the first time index when predictions satisfy β -criterion for a given α

$$\min \left\{ k \mid (k \in p) \wedge \left(\pi[r(k)]_{-\alpha}^{+\alpha} \right) \geq \beta \right\}$$

p is the set of all time indexes when predictions are made

l is the index for l^{th} unit under test (UUT)

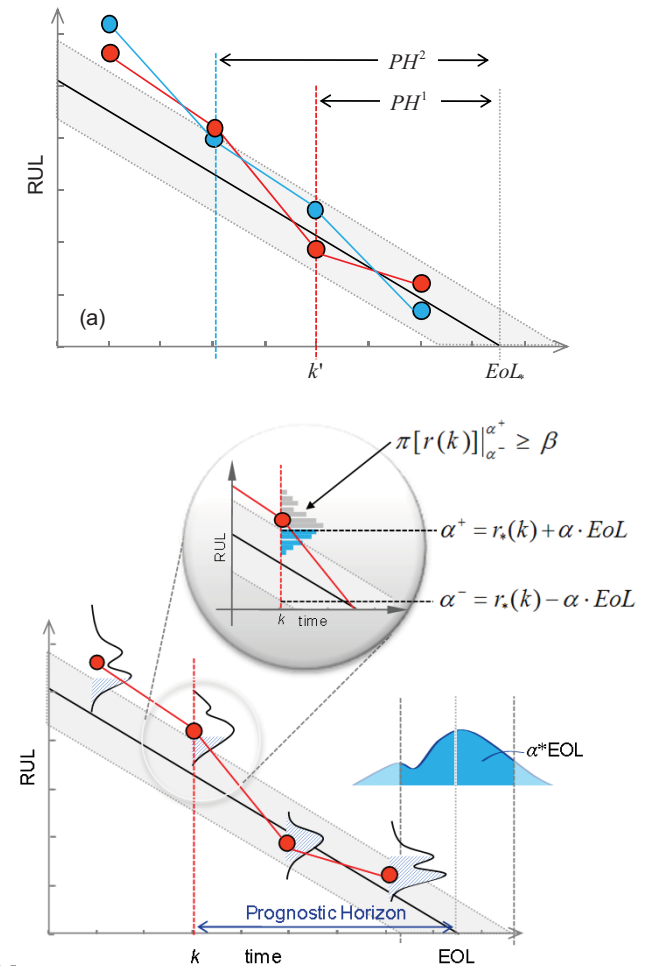
β is the minimum acceptable probability mass

$\pi[r(k)]_{-\alpha}^{+\alpha}$ is the probability mass of the prediction between α -bounds given by $\alpha^+ = r_*(k) + \alpha \cdot t_{EoL}$ and $\alpha^- = r_*(k) - \alpha \cdot t_{EoL}$

$r(k)$ is the predicted RUL distribution at time t_j

t_{EoL} is the predicted End-of-Life

The range of PH is between $(t_{EoL} - t_P)$ and $\max[0, t_{EoL} - t_{EoP}]$



α - λ Accuracy

- **α - λ Accuracy** determines whether at given point in time (specified by λ) prediction accuracy is within desired accuracy levels (specified by α). Desired accuracy levels for ant time t are expressed a percentage of true RUL at time t .

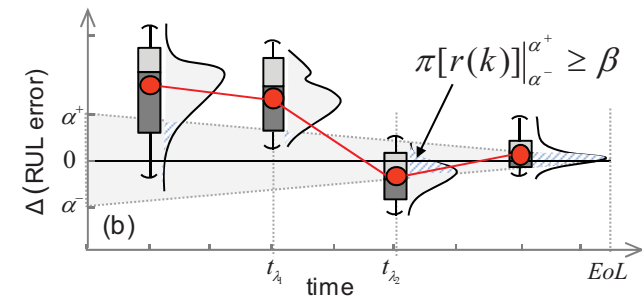
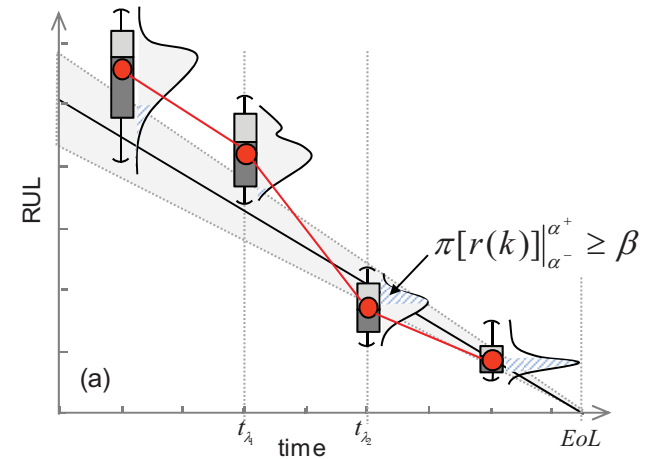
$$\alpha - \lambda \text{ Accuracy} = \begin{cases} 1 & \text{if } \pi[r(i_\lambda)]_{-\alpha}^{+\alpha} \geq \beta \\ 0 & \text{otherwise} \end{cases}$$

λ is the time window modifier such that $t_\lambda = t_P + \lambda(t_{EoL} - t_P)$

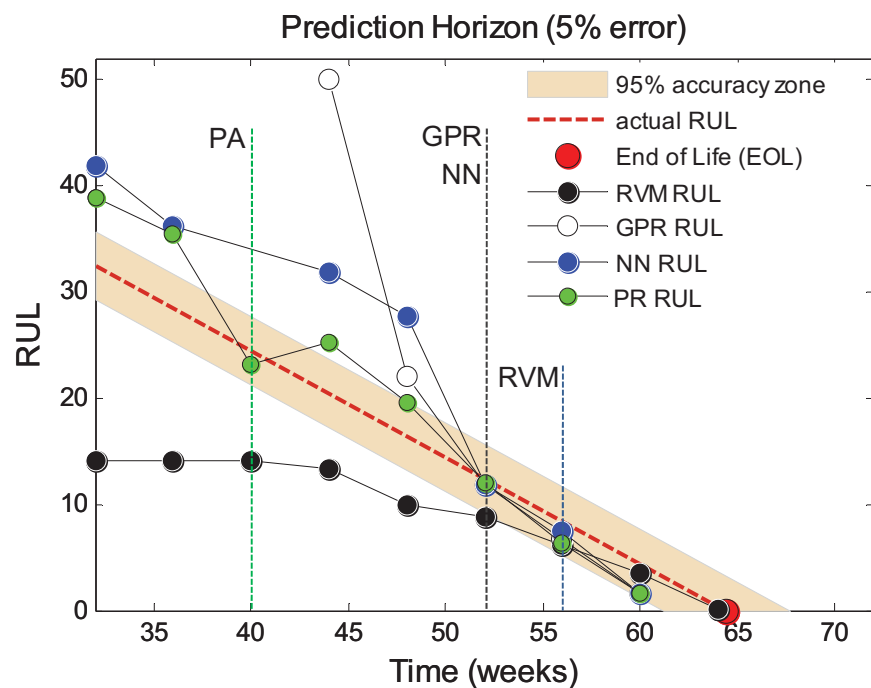
β is the minimum acceptable probability mass

$r(i_\lambda)$ is the predicted RUL at time t_λ

$\pi[r(i_\lambda)]_{-\alpha}^{+\alpha}$ is the probability mass of the prediction between α -bounds given by $\alpha^+ = r_*(i_\lambda) + \alpha \cdot r(i_\lambda)$ and $\alpha^- = r_*(i_\lambda) - \alpha \cdot r(i_\lambda)$

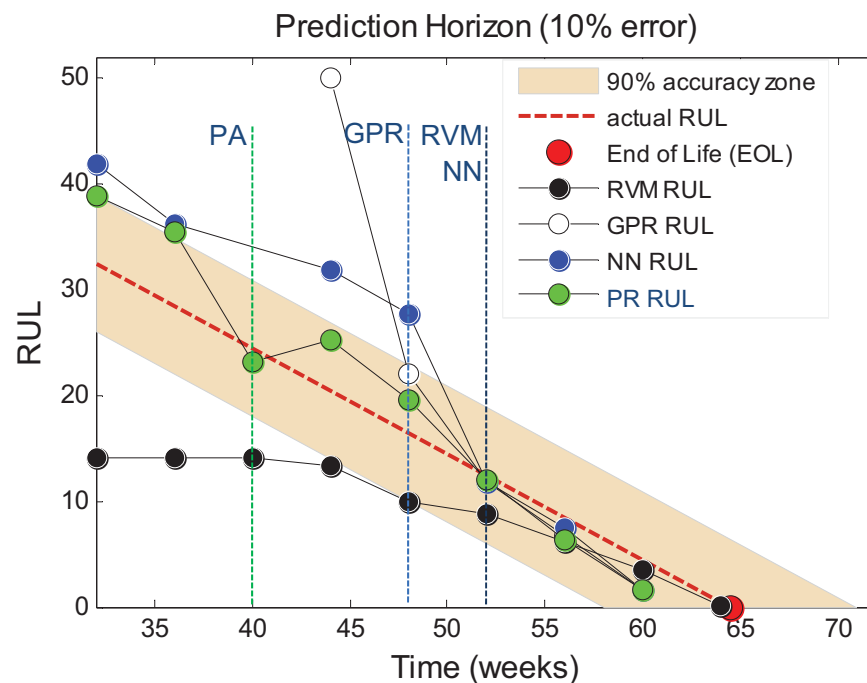


Comparing Various Algorithms



	RVM	GPR	ANN	PR
PH (weeks)	8.46	12.46	12.46	24.46

$PR > GPR = ANN > RVM$



	RVM	GPR	ANN	PR
PH (weeks)	12.46	16.46	12.46	24.46

$PR > GPR > ANN = RVM$